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CALENDAR ANOMALIES: EVIDENCE FROM SIX EMERGING MARKETS

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Abstract

This study aims to examine the presence of three well-documented calendar anomalies: The January/monthly, turn-of-the-month and day-of-the-week effect. These anomalies refer to systematic variations of financial asset returns during certain times of the week, month, or year. Throughout decades, these stock return regularities have been considered as decisive counterexamples that deviate from efficient market hypothesis due to potential trading strategies that generate abnormal returns based on such seasonal variations.

Most explanations on the appearance of calendar anomalies are related to behavioural finance framework. Thus, investors might base their investment decisions on behavioural characteristics such as overconfidence and loss avoidance. However, recent research suggests that seasonal effects are disappearing in stock markets. The disappearance of calendar anomalies is a result of market learning, and therefore the exploitation of stock return seasonality has become less prominent. Based on the market efficiency theory, behavioural anomalies should be arbitraged away in the long run when investors begin exploiting them (Fama, 1998).

This thesis aims to examine the behavior of stock return seasonality in six emerging market exchanges during the period of January 2005 through December 2020. Since numerous emerging market exchanges are open for foreign investors and they have experienced a rapid growth in recent years, the interest of observable anomalies is highlighted. The widely popular January/monthly, turn-of-the-month and day-of-the-week effects are estimated with the commonly used dummy variable regression model. In addition, all three are estimated with the GARCH framework by incorporating volatility clustering and asymmetric responses of return volatility.

The OLS results show that the turn-of-the-month effect is statistically significant in Prague, Budapest, and Malaysian stock exchanges. The effect is also significant based on the GARCH regression results. Moreover, based on the OLS results, a weekend effect is found in the Malaysian stock exchange, where Friday returns are significantly high, and Monday returns significantly low. Under the GARCH framework, a January effect is found only in the Prague stock exchange. This indicates that the anomaly has most likely disappeared. Furthermore, the GARCH regression results exhibit positive Monday effects for Prague, Warsaw, and Johannesburg exchanges. Thus, the mixed results of the January/monthly effect and the day-of-the-effect indicate that they are sensible to the choice of error distribution, and generalizations of their existence cannot be made. However, the asymmetric GARCH models exhibit similar results by accounting the volatility dynamics to a greater extend. Thus, seasonality in the examined emerging market returns is present.

Keywords
Calendar anomalies, Emerging markets, Efficient Market Hypothesis, Behavioral Finance

Additional information

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1 INTRODUCTION

Conventional finance theory assumes that financial markets are complete and efficient. It suggests that investors are conscious of the fundamental value of an asset, and all the available and existing information reflects the price of an asset. According to the original theory, an individual or an institutional investor makes investments decisions rationally and thus does not allow various psychological factors to affect investment decisions. The investment activities of a rational investor are guided by her own preferences and the goal of an investment is to maximize profits.

Multiple inefficiencies and distortions in asset prices have been found that the conventional theory cannot explain. Investors have been driven by their emotions and other psychological factors and might not act rationally. As a result, the foundation of behavioural finance has provided explanations for irrational investment behaviour. The behavioural theory seeks to provide more humane interpretations of market and investor behaviour that the traditional financial theory cannot explain with rational assumptions.

Many financial and economic variables seem to have periods where the behavior of the series changes quite dramatically compared to previous observations. The behavior of series may change over time to its average value, volatility, or the extent to which the current value relates to its past value. The transformation of the behavior in a series might be permanent, meaning that a “structural break” occurs, or the change might be temporal as the series returns to its previous behavior. In the context of financial markets, seasonal effects have been widely studied. It has often been documented that some financial variables regularly exhibit different values for some periods than others. Especially in equity markets, the turn-of-the-month effect, the January/Monthly effect and the day-of-the-week effect are well-documented calendar effects or calendar anomalies. (Brooks, 2019, p.447-449.)

According to Van der Sar (2003), the lack of rational investors is causing calendar anomalies because fundamental factors are not the basis for investment decisions but simple valuation methods or other irrelevant factors. Thus, it is essential to understand these reasons for justifying the observed patterns and making predictions of market movements. (Van der Sar, 2003.)

This thesis aims to examine three widespread calendar effects that have been widely studied over a long period. The effects are the January effect, turn-of-the-month effect, and day-of-the-week effect. Recently, researchers have found that many calendar anomalies have disappeared (Cochrane, 1999, Marquerin et al., 2006, Shanaev & Ghimire, 2021). However, much research supporting the existence of calendar anomalies has been published mainly for emerging markets (Patel, 2016, Volkan, Kayacetin & Lekpek, 2016, Chiah & Zhong, 2019). Furthermore, since most recent financial studies employ the framework of volatility modelling, this thesis uses similar techniques to enhance the adequacy of results. Thus, the significant differences in returns on different periods may be attributable to time-varying volatility.

Although the topic of stock market anomalies has been extensively studied in developed markets, the subject has recently received a lot of attention in emerging markets. Many emerging markets have different trading structures, and they might not observe the same trading days or religious holidays as many developed markets. According to Harvey (1995), the dynamics of emerging markets differ substantially from developed markets in terms of expected returns and volatility. The high autocorrelation of stock returns induces part of the predictability of emerging market returns. The low asset diversification of emerging market indices can cause serial correlation in the index returns. (Harvey, 1995.)

Furthermore, volatility in emerging markets depends on many different factors. In fully integrated markets, global factors strongly impact volatility, whereas local aspects significantly impact volatility in segmented markets (Bekaert and Harvey, 1997). Due to these structural differences, it will be interesting to see if any of the three calendar anomalies examined in this thesis occur in individual emerging markets. Re-examination of calendar effects in emerging markets is essential, as their data are studied less frequently and constantly developing.

This thesis is constructed as follows: Section 1 introduces the topic. In the second section, market efficiency and random walk theories are discussed. Section 3 accounts for issues of behavioural finance and modifications for market efficiency theories. Section 4 introduces calendar anomalies, such as the January effect, Turn-of-the-month effect, and Day-of-the-week effect. Section 5 introduces the empirical part of the thesis, presenting the data and methods which are conducted to obtain the results in chapter 6. Empirical results are analyzed in chapter 6. Chapter 7 concludes the thesis by presenting results and possible explanations based on the empirical results compared to previous findings. In addition, further research problems are presented.

2 MARKET EFFICIENCY

The concept of efficient markets and return predictability was initially introduced in 1900, when mathematician Louis Bachelier published his book *The Theory of Speculation.* This book was the first of its kind to explain how the stock market works in general. According to Bachelier's study, security prices are unpredictable because historical, present, or even discounted current events do not affect changes in stock prices. In the study, Bachelier argues that probability of a change in market prices, either up or down, is identical. Stock prices change when there is an incentive in the market to change their prices, but no one can predict in which direction the price changes move as the probabilities are identical. (Bernstein, 1993.)

2.1 Efficient Market Hypothesis

Efficient Market Hypothesis (EMH) means that all market information is included in the price of the securities. Thus, any information that could be used in stock return prediction should already be reflected in stock prices. When there is any information implying that a stock is priced with a discount and therefore offers an opportunity for profits, investors tend to buy that stock and instantly bid up the price to a correct level. Expected returns rates are commensurate with the risk of the stock. (Fama, 1970, Bodie, Kane & Marcus, 2018, p.334).

According to Fama (1970), certain conditions are needed for an efficient market to succeed. Firstly, it is assumed that in an efficient market, there are no brokerage fees. The second assumption is that all market information is available for free to each party. The last assumption is that each market participant should have the same expectation on the current and future values of stock prices. The market is efficient, should these assumptions hold. (Fama, 1970).

The efficient market hypothesis is divided into three versions according to how well security prices reflect different types of information. The various forms of market efficiency are weak, semi-strong, and strong, ranging from the most inefficient to the most efficient. In the transition from weak to strong form, security prices always reflect information more versatile and efficient than in the previous form. The extent determines market efficiency to the information prevailing in the financial markets is priced in the securities. (Bodie, Kane & Marcus, 2018, p.337.)

Based on the weak-form hypothesis, security prices reflect information, such as historical price data, trading volume, or short interest. Thus, investors cannot use technical analysis to predict future stock prices and achieve abnormal returns. The weak-form hypothesis states that there are no patterns in stock price series, indicating that future price fluctuations are not determined by price series information. However, negative, and positive correlations have been documented for changes in stock returns between consecutive days to a small extent. Still, these observations are not considered highly significant in both statistical and economic sense. Thus, there is no strong evidence of long-term correlations of past stock returns. (Fama, 1970.)

Early tests of weak form conditions observe trends in stock prices by measuring the serial correlations of returns in stock markets. Serial correlation implies the tendency in which current stock returns are related to previous returns. If the serial correlation is positive, then positive returns generally follow positive returns (momentum). Negative serial correlation refers to a phenomenon in which positive returns are generally followed by negative returns (Bodie, Kane & Marcus, 2018, p.349). Weekly returns of NYSE stocks have been studied by Conrad and Kaul (1988) and Lo and MacKinlay (1988), in which the findings suggest a positive serial correlation over short periods. However, the correlation coefficients seem to be relatively small, indicating no apparent trading opportunities as they demonstrate weak price trends over short horizons (Lo and MacKinlay 1988; Conrad and Kaul 1988).

The semi-strong form hypothesis asserts that stock prices should already reflect all publicly available information regarding companies' information. In addition to historical data, information includes, for instance: quality of management, forecasted earnings, balance sheet composition, patents held, and accounting principles (Bodie, Kane & Marcus, 2018, p.338). Thus, it is impossible to earn excess returns by utilizing fundamental analysis, as all information is already included in the stock price. Researchers have studied the semi-strong of the efficient market hypothesis by measuring how quickly stock prices respond to different types of news regarding earnings and dividend announcements. Fama (1970) studies hundreds of stock splits over thirty years and finds stock prices increasing immediately after splits announcements. Thus, the market interpreted splitting as a positive sign, as 71,5 percent of companies that announced a stock split later raised their dividends more than the New York Stock Exchange on average (Fama, 1970).

The strong-form hypothesis states that all relevant firm-specific information, even inside information, is reflected in stock prices. This kind of information is only available to a particular investor or group of investors. Corporate managers or insiders may have access to information that is not available to the public and could earn excess returns by trading on that information. Financial regulations and most of the activities of regulatory authorities aim to constrain insider trading. (Bodie, Kane & Marcus, 2018, p.338.)

According to Finnerty (1976), the strong-form conditions can be tested by examining how the returns of investors who have access to inside information differ from investors who do not have access to inside information. Investors with monopolistic information usually earn higher than average returns. Thus, contrary to theory, it is possible for investors with inside information to beat the market by taking advantage of their broader knowledge of the market, in which case the market is not efficient. Insider information has an impact on the entire market when other investors follow investors who exploit insider information. (Finnerty, 1976.)

According to Lo (2004), prices, probabilities, and preferences constitute the “three P’s of total investment management,” generalizing the current EMH paradigm. The origins of the three P’s come from the fundamental doctrines of economic theory, demand, and supply. An “equilibrium” is defined as the intersection of these two curves representing a price-quantity pair that simultaneously satisfies both consumers and producers. The demand curve forms the aggregation of many consumers’ wishes, each derived from the optimization of consumer’s preferences subject to a budget constraint that depends on income and prices. Equivalently, the supply curve is the aggregation of many producers’ quantities, each derived from the optimization of entrepreneur’s preferences subject to a resource constraint that depends on prices and costs of manufacturing. In addition, probabilities affect both producers and consumers as they make their production and consumption plans over time under uncertain conditions. In the context of financial economics, many formal models of asset pricing have been developed, which all show how a "general equilibrium" has been determined by the three P's. (Lo, 2004.)

2.2 Random Walk Hypothesis

The theory of random walks in stock prices has a long history and perhaps the earliest well-known paper was published in 1953 by Maurice Kendall. Afterwards, the random walk hypothesis has been tested in numerous studies and its theory has been reformed by many academics. Kendall (1953) observed that no predictable patterns can be made on stock prices as they move randomly. This implies that future price changes of a security do not depend in any way on its previous price changes. (Fama, 1965). Fama (1995) argues that the random walk hypothesis is strongly related to an efficient market in which numerous rational investors seek to predict the prices of individual securities in the future. Because current information in the market is almost freely available to all, competition between many investors causes securities prices to reflect the effects of current and past information at any given time. (Fama, 1995.)

Studies from Keim and Stambaugh (1986), Fama and French (1987), and Lo and MacKinlay (1988) have revealed that stock returns comprise predictable components. Thus, the behaviour of stock returns is not entirely random. For instance, Keim and Stambaugh (1986) show that predetermined variables representing bond and stock prices can predict stock prices of different firm sizes and bonds with different maturities. Fama and French (1987) discover significantly negative autocorrelation in extended holding-period returns, indicating that the variation of long holding-period returns is predictable from previous returns. Lo and MacKinlay (1988) apply the logic of variance scaling to test the random walk hypothesis by proposing a variance ratio test. The authors reject the hypothesis of random walks in weekly stock returns and conclude that time-varying risk and infrequent trading cannot completely explain the rejections. In contrast to the findings of Fama and French (1988), Lo and MacKinlay (1988) report positive autocorrelation for extended holding-period returns.

The random walk hypothesis has also been studied in emerging markets. For instance, Smith and Ryoo (2003) report significant autocorrelation in the returns of four markets: Greece, Hungary, Poland, and Portugal. The hypothesis that stock returns follow a random walk is not rejected in Turkey, the Istanbul stock market. The most important factor that seems to have effective power to random walks is liquidity since liquidity is much greater on the Istanbul stock market than in any other markets in the sample. In addition, the price formation process is more active in Istanbul than in other markets in the sample, indicating weak-form efficiency. (Smith & Ryoo, 2003.) Moreover, Al-Khazali, K.Ding, and Pyun (2007) revisit the empirical validity of the random walk hypothesis and document that stock returns in North Africa and the Middle East follow random walk procedure after adjusting the data for infrequent trading. Thus, these results indicate different implications of infrequent trading compared to the findings of Lo and MacKinlay (1988).

3 BEHAVIOURAL FINANCE

Traditional finance theory does not consider how people operate and make decisions in the real world. Investors make complex decisions in financial markets, and the behavior is not always rational. Investors' information process is not always correct, and therefore they make erroneous conclusions about the probability distribution of expected returns. In addition, investors often make inconsistent or systematically suboptimal decisions, even if they know the probability distribution of stock returns. The presence of irrational investors in the market does not mean that the market must be inefficient. According to the efficient market hypothesis, arbitrageurs take advantage of irrational investors' opportunities and drive prices back to their correct level. Thus, behavioral finance criticizes traditional finance theory because arbitrage possibilities are limited and involve risk. (Bodie, Kane & Marcus, 2018, p.389.)

3.1 Behavioral biases

Kahneman and Tversky (1974) show that people tend to emphasize recent experience compared to previous beliefs when making predictions. Generally, predictions are too extreme given the uncertainty associated with their current information. DeBondt and Thaler (1990) suggest that overly extreme earnings expectations can explain the Price-to-earnings (P/E) effect. In this sense, when predictions of a company’s earnings in the future are high, perhaps due to recent good performance, they are usually too high compared to objective views about the company. This might lead to a high initial P/E and subsequent underperformance when investors realize their mistakes. Therefore, companies with high P/E multiplies may be bad investments. (Kahneman & Tversky, 1974, DeBondt and Thaler.)

Overconfidence relates to a behavior in which people tend to overestimate their abilities in forming forecasts. Barber and Odean (2001) study men’s and women’s trading activity and average returns in their brokerage accounts. The findings suggest that active trading is done far more by men than women. The results also indicate that active trading leads to bad investment performance. The average return of the largest quintile of accounts classified by portfolio turnover is 7 % lower than the lowest quintile by turnover rate. In corporate finance studies, overconfidence seems to exist strongly among CEOs. For instance, Malmendier and Tate (2008) argue that CEOs with high overconfidence are more likely to pay too much for target companies when making mergers and acquisitions. (Barber & Odean, 2001, Malmendier and Tate, 2008.)

The representativeness bias implies that investors generally do not consider the sample size because a small sample only represents a large population. Therefore, they can deduce the model too quickly from a small selection and extrapolate the apparent trends too far into the future. It is easy to see how much such a model would be consistent with overreaction and correction deviations. An excellent short-term earnings report or a high share price would lead such investors to revise their estimates of likely future developments and thus create buying pressures that exaggerate price increases. In the end, the gap between the market price and intrinsic value becomes noticeable, and the market revises the price to its correct level. In turn, stocks that had performed well recently suffer from disclosure within just a few days of earning announcements, suggesting that the correction occurs just when investors learned that their initial beliefs were too extreme. (Bodie, Kane & Marcus, 2018, p.391.)

Even though information processing was idealistic, numerous studies show that people tend to make less than entirely rational decisions with that information. These behavioral biases have a significant impact on the framing of investors' questions about risk-return trade-offs. The framing of choices seems to influence decisions. Individuals can be risk-averse when facing choices that involve gains but risk-seeking with options that include losses. However, the framing of gains and losses can be arbitrary in many cases. A specific form of framing is mental accounting, in which individuals segregate decisions. For example, an investor may open an investment account in which she invests very conservatively by raising funds for her children's education. At the same time, she may have another account in which she makes very risky investments, by seeking quick profits. (Thaler, 1999, Bodie, Kane & Marcus, 2018, 391.)

Regret avoidance reflects individuals' reluctance to suffer losses from unconventional investment decisions. For example, the losses that occurred on an unknown start-up firm are more painful than similar losses on a portfolio that consists of blue-chip stocks. According to DeBondt and Thaler (1987), the size and book-to-market effect relate to regret avoidance since firms with higher book-to-market ratios tend to have depressed stock prices. This effect is also consistent with mental accounting when investors focus more on the gains or losses of individual stocks rather than on broadly diversified portfolios. As a result, they become risk-averse considering stocks with recent bad performance, use a higher rate at discounted cash flows, and create a risk premium for value stocks. (DeBondt & Thaler, 1987, Bodie, Kane, & Marcus, 2018, 392.)

Perhaps the most well-known behavioral bias is the prospect theory developed by Kahneman and Tversky (1979). In the conventional utility function, utility depends on wealth and increases at a diminishing rate as wealth increases. On the other hand, in the utility function under prospect theory, utility depends on the changes in wealth from current levels. Thus, the utility curve is convex to the left of zero (denotes no change from current wealth) rather than concave. While many conventional utility functions relate to investors' decreased risk aversion due to increased wealth, the prospect theory always focuses on current wealth, which precludes a reduction in such risk aversion and perhaps helps explain high average historical equity premiums. (Kahneman & Tversky, 1979, Bodie, Kane & Marcus, 2018, 393.)

3.2 Limits to Arbitrage

The first condition of the EMH relates to a situation in which investors are assumed to be rational and evaluate their investments based on the mean and variance. The EMH does not require rationality on all investors; for instance, irrationality is permitted if irrational investors' trading activities do not correlate with each other. In such cases, the actions taken by irrational investors tend to cancel each other out, and market prices are unaffected. Suppose the trading by irrational investors is correlated. In that case, the third condition/assumption of EMH states that rational investors will practice arbitrage (i.e., earn a risk-free profit) and correct the prices in the process. It is assumed that due to the actions of irrational investors, the price of a particular stock will rise above its true fundamental value, making the stock a bad investment target when its price exceeds its future risk-adjusted net present value. As a result, rational investors take advantage of the arbitrage opportunity by selling or even short selling the overpriced stock, and at the time, buying a similar but correctly priced stock as a replacement investment. (Shleifer, 2000, p.1-4.)

According to Shleifer (2000), behavioral finance theory has challenged the efficient market hypothesis and its conditions with both theoretical and empirical evidence. Many investors form their expectations about returns based on irrelevant information. If the efficient market hypothesis were based solely on individual investors' rationality, psychological evidence could already reject the theory. Under the second condition, however, the view allows an approach from rationality as long the actions of irrational investors are random, and thus their effects cancel each other out. Psychological evidence shows that similar factors drive investors' deviations, and they tend to cluster. (Shleifer, 2000, p.10-12.)

The third condition of the efficient market hypothesis is based on the possibility of arbitrage by rational investors and how their actions correct the price distortions caused by irrational investors. For an arbitrage opportunity, substitution stocks should be available in the market for stocks whose prices have the potential to have a noise trading effect and are therefore mispriced. Although a lot of trading is required for discovering arbitrage, for some derivatives such as options and futures, close substitutes are available. Typically, for example, the S&P 500 index futures’ prices are set close to the value of the underlying stocks, because if there is much deviation between the future price and the price of the underlying asset, an arbitrageur could take advantage by purchasing whichever is cheaper and selling against it whichever is more expensive. In addition, if one could find a substitute asset, the pricing error may worsen before it disappears. Consequently, the arbitrageur will suffer temporary losses due to margin requirements in leveraged trades. (Shleifer, 2000, p.13.)

One crucial factor associated with limits to arbitrage is the fundamental risk. Assume that a stock is priced below its intrinsic value. Purchasing might offer an opportunity to make a profit, but it still includes risk since the undervalued stock may lower further. Even though the price should bounce back to its intrinsic value, this might occur only after the investor’s investment horizon. For instance, the investor may manage a portfolio in a mutual fund, and if the fund is underperforming, the investor might lose clients. Thus, the fundamental risk associated with exploiting specific profit opportunities is likely to limit the activity of traders in financial markets. (Schleifer & Summers 1990, Bodie, Kane & Marcus 2018, p.394.)

3.3 Adaptive Market Hypothesis

Andrew Lo (2004) introduces a new framework for market efficiency by applying theories of behavioral science. This perspective highlights principles of evolution, such as competition, adaption, and natural selection in financial interactions. According to Lo (2004), there are intersections between behavioral biases and the evolutionary model. People adapt to a changing environment using heuristics, which are approaches to solving various problems based on people's assumptions and experiences from a pragmatic perspective. (Lo, 2004.)

The critical theory of the adaptive market hypothesis (AMH) is that market efficiency is dynamic and dependent on the context. Thus, the degree of market efficiency is affected by environmental factors, such as the number of market participants and their adaptability, competition, and the magnitude of available profit opportunities. If several market participants compete for relatively scarce resources within a single market, then it is likely for that market to be highly efficient. By contrast, if a small number of market participants are competing for relatively abundant resources, it is expected for that market to be less efficient. (Lo, 2004.)

The AMH has several implications caused by innovation and competition between individuals as they learn from mistakes and adapt to the environment. Firstly, the stock market environment and demographics of investors induce varying risk premiums over time. Secondly, as arbitrage opportunities are discovered and exploited, the market environment does not directly move to a higher degree of efficiency despite that the arbitrage opportunities disappear. The AMH implies that new profit opportunities are constantly generated due to complex market dynamics such as trends, bubbles, panics, and crashes. Thirdly, investment strategies such as exploiting calendar anomalies might weaken for a time but revive once environmental conditions become more feasible to such strategy. (Urquhart & McGroarty, 2014.)

4 CALENDAR ANOMALIES

Calendar anomalies have been well-observed phenomena in academic research in finance. For instance, the January, day-of-the-week, and turn-of-the-month effects are widely studied calendar anomalies (Thaler, 1987a). These anomalies are defined as seasonal patterns at specific periods as they tend to show significantly positive or negative stock returns on a day, week, month, or year. Therefore, calendar anomalies may provide profitable trading strategies. However, recent research shows that abnormal returns generated by exploiting calendar anomalies are disappearing in developed markets (Shanaev & Ghimire, 2021; Marquering et al., 2016). Based on the weak-form EMH and market learning theory, behavioral market anomalies decay in the long-term as investors become more aware of them and begin to take advantage of them (Fama, 1998, Timmerman & Granger, 2004). Nevertheless, many researchers still suggest that calendar anomalies may be present for a short period, but the significance of the anomalies varies highly between different stock markets.

4.1 January/Monthly effect

Evidence against the random walk behavior has been documented with a so-called January effect, in which stock prices tend to increase from December to January (Wachtel, 1942; Rozeff & Kinney, 1976; Keim, 1983; Reinganum, 1983). Commonly, the effect occurs since investors are incentivized to sell their loss-making stocks in December to reduce their tax liability by deducting capital losses from other capital gains.

Sidney B. Wachtel (1942) is the first to observe the January effect when studying the price development of the Dow Jones Industrial Average from 1927 through 1942. Wachtel's findings indicate an apparent rise in the index as the year turns from December to January. He finds that the value of the index rises significantly from December to January. Wachtel suggests the tax-loss selling hypothesis as an explanation for the January effect. It relates to investor behavior, in which investors sell their loss-making stocks at the end of the year, which will result in the prices of those stocks decreasing. At the turn of the year, the sale of the loss-making stocks ends, as the tax benefits have already been earned through the December stock sale. Thus, the January excess returns occur since the market returns to its normal state. (Wachtel, 1942.)

Rozeff and Kinney (1976) exploit Wachtel's findings to study stock market seasonality in the US. The authors examine monthly returns of the New York Stock Exchange (NYSE) equal-weighted index from 1904 through 1974. The authors detect statistically significant higher average returns in January relative to other months except from 1929 to 1940. The higher return in January can be explained by new information that firms typically provide at the end of the year. Based on this news, investors will sell and buy their stocks according to the information. In January, the reports regarding companies' financial earnings are often published, providing even more information for investors to respond. (Rozeff & Kinney, 1976.)

Keim (1983) examines the relationship between firm size and the January effect using NYSE and the American Stock Exchange (AMEX) from 1963 through 1979 as data samples. Keim's (1983) findings suggest that the distributions of daily abnormal returns in January have more prominent means than the other eleven months. In addition, Keim (1983) argues that there is a negative relation between abnormal returns and size, and it is more precise in January than in other months. In other words, small-capitalization firms are more likely to generate abnormal returns than large-capitalization firms. This phenomenon is evident even in years when, on average, larger firms generate higher risk-adjusted profits than small firms. Throughout 1963 through 1979, nearly fifty percent of the average magnitude of the "size effect" is due to abnormal returns in January. Moreover, more than fifty percent of the premium in January is due to significant abnormal returns occurring at the first trading week of the year, especially during the first trading day. (Keim, 1983.)

Reinganum (1983) detects similar findings regarding the relationship between small-capitalization firms and significant excess returns in January. Exceptionally high returns in January and during the first trading days of January are generated by small firms. Based on the empirical findings, the abnormally high returns observed in early January appear to be due to tax-loss selling. Nevertheless, the January effect cannot be explained entirely by the tax-loss selling hypothesis. (Reinganum, 1983.)

Gultekin and Gultekin (1983) examine the seasonality of stock markets in large industrialized countries throughout January 1959 through December 1979. The authors find evidence that stock market returns fluctuate sharply during different seasons in most capital markets around the world. In most countries, disproportionately high January returns appear to cause seasonal fluctuations, and April returns seem to cause similar effects in the UK. The tax year in the UK begins in April and ends in March. Thus, the tax-loss selling hypothesis has explanatory power concerning the April effect in the UK. The authors use Capital International Perspective (CIP) data, providing end-of-the-month prices of the value-weighted indices in local currency. Although there appear to be significantly high average returns at the turn of the year, the authors conclude that size-related anomaly is not related to these calendar effects. (Gultekin & Gultekin, 1983.)

Although the tax-loss selling hypothesis has been considered a significant factor in explaining the January effect, international evidence reveals that tax-loss selling cannot be the only explanation. Non-citizens trading in countries with no capital gains tax or different tax years and are subject to January-based taxes could explain the January effect in these countries, but little evidence supports this argument. Moreover, research has found evidence that Japanese and US stock prices are slightly correlated, which undermines the arguments of tax-loss selling substantially. Nonetheless, returns at the beginning of the tax year in many stock markets are high, so taxes have some effect. (Thaler, 1987a.)

Another necessary explanation for the January effect is the insider-trading/information-release hypothesis. The mechanism related to this hypothesis is that, as most firms' fiscal year starts on January 1 and ends on December 31, management will receive non-public information at the beginning of January. Some managers may use this information to invest in which investors on the other side of the transaction experience losses, on average. Therefore, these investors require a higher rate of return to protect themselves, which causes the January effect. However, the insider-trading/information-release hypothesis does not predict the observed pattern that small firms that have experienced price declines in the past have more significant returns in January than other firms, on average. (Ritter, 1988.)

Ritter (1988) suggests that individual investors' buying and selling behavior is the cause of the January effect. Part of the sales proceeds will not be reinvested immediately because the securities are realized for tax purposes at the end of the year. Still, it will instead be "parked" until January. The reinvestment of these funds thus raises the price of small firms, which individual investors typically invest in. For institutional investors, there are no incentives to be involved in investment activities based on tax-motivated purchasing and selling. (Ritter, 1988.)

Ritter (1988) examines individual investors' buying and selling behavior at the turn of the year by making a unique set of data that includes the daily buy/sell ratios of the clients of the cash accounts of the largest brokerage firms in the US. The analysis consists of daily returns from CRSP prices of the fifteen turn-of-the-year periods from December 1970 through December 1985. The main findings indicate that with the utilization of individual investors' buy/sell ratio, the net selling in December abruptly shifts to net buying at the turn of the year. The behavior of the buy/sell ratios is consistent with the tax-loss selling hypothesis and the small firm effect, in which individual investors realize losses for tax purposes by selling stock that has decreased in price during December. However, reinvestment does not happen immediately; instead, investors wait until January, when they invest in a wide range of small stocks. (Ritter, 1988.)

Haugen and Jorion (1996) find similar empirical results on the relationship between the January effect and small firm returns. They argue that the price disturbance at the end of the year of small stocks is arguably the most well-known anomaly documented in the stock market during the 1970s and 1980s. However, the authors show that the magnitude of the effect has not changed significantly, and no remarkable trend indicates its final disappearance. The authors examine all stocks of the NYSE in the CRSP monthly data file from 1926 through 1993 by ranking the stocks based on total capitalization. The time series regressions show that small firms, based on size deciles, have a more substantial impact on the January effect than large-capitalization firms. (Haugen and Jorion, 1996.)

Bhardwaj and Brooks (1992) argue that the January effect cannot be exploitable due to higher transaction costs of small, low-priced stocks. According to the authors, higher transaction costs and bid-ask bias potentially explain the failure of informed investors to eliminate significant before-transaction-cost excess returns in January. Therefore, the January effect is not likely to be an ongoing and exploitable trading strategy. (Bhardwaj and Brooks,1992.)

By contrast, according to Haugen and Jorion (1996), individual investors can exploit the January effect as a trading strategy through mutual funds. The marginal cost of trading resulting from the transition of mutual funds from the money market account to the small-cap stock account at the end of the year is unlikely to prevent such companies from taking advantage of the January effect. This is because transaction costs are shared with all mutual fund participants. Market neutrality can be achieved by taking long positions in approximately equally weighted or small stock indices, such as the Russell 2000 index, and simultaneously taking short positions in capital-weighted indices, such as the S&P 500. (Haugen & Jorion, 1996.)

Szakmary and Kiefer (2004) analyze returns of cash indices and futures relative to the S&P 500 to track smaller stocks at the turn of the year. In addition, the authors control for volatility clustering, autocorrelation of small stock index returns, and other calendar anomalies to provide robust estimates of the January effect. The data used in the study includes returns of portfolios combining long positions in the Value Line, S&P 400 Midcap, and Russell 2000 cash indices and futures, respectively, with a short position in the S&P 500 index. In this case, the indices of the long position portfolio are used as a proxy for the small-capitalization sector, since these indices track smaller stocks than the S&P 500. The authors find that market participants are seemingly eliminating the January effect with the exploitation of two new futures contracts on small-capitalization indices (the S&P Midcap 400 and Russell 2000 futures). Based on the results, after June 1993 the returns of the long position portfolio combined with short positions in the S&P 500 index are much lower during the traditional turn of the year window (last trading day of December and first five trading days in January). (Szakmary and Kiefer, 2004.)

Cooper, McConnell, and Ovtchinnikov (2006) explore the predictive power of January returns over the period 1940-2003 for the rest of the year conditional on the January market return. The authors use an alternative approach to test this so-called "the other January effect" by controlling for macroeconomic/business cycle variables that have been shown to have a predictive effect on stock returns. In addition, the Presidential Cycle, investment sentiment, and different multifactor models are controlled for in the analysis. Authors' results indicate that over the following 11 months of the year, January stock returns are a remarkably robust predictor of market returns. When the CRSP value-weighted index return in January is positive, over the next 11 months, the index's average return is 14.8 percent. When the value-weighted index return is negative in January, the index's average return over the next 11 months is 2.92 percent, causing a spread of almost 12 percent. Even a larger spread of 18 percent is observed from the equal-weighted index returns. Each of these spreads is economically and statistically significant. The authors find that the market and size premium returns are positive for the remainder of the year when January returns are positive. On the contrary, the market and size premium returns are negative for the rest of the year when January returns are negative. In both cases, the spreads are statistically significant. (Cooper, McConnel & Ovtchinnikov, 2006.)

Patel (2016) investigates both developed and emerging stock markets from January 1997 through December 2014. The empirical results are contradictory compared to previous studies since the returns in January are insignificant. Moreover, different volatility periods do not cause the January effect in each of the six indices. Notably, in most indices, returns in January are relatively lower than returns on the other eleven months since positive returns in January are generated only by the emerging stock and Russell 3000 index. Still, the January returns are not the highest compared to other months' returns in the emerging stock and Russell 300 index. However, the study reveals significantly positive returns in April in three out of six indices and in December in four out of six indices. (Patel, 2016.)

4.2 Turn-of-the-month effect

One significant extensively studied calendar anomaly is related to significantly high stock returns during the month's last trading days and the first few trading days of the following month. Ariel (1987) first documented this so-called turn-of-the-month anomaly (TOM). The author investigates seasonal patterns of daily CRSP value-weighted and equal-weighted stock index returns from 1963 – 1981. Empirical results show that the average return on the month's last trading day and the first half of the following month is positive and significantly different from zero. In contrast, the average return is even negative in the second half of the month. (Ariel, 1987.)

Further, Lakonishok and Smidt (1988) analyze the evidence of monthly regularities using a similar method to Ariel (1987) by adding little new data for the monthly seasonality. The authors point out that it is crucial to use new data on hypotheses testing since it avoids data-snooping. The data-snooping bias is related to a practical problem, in which many different hypotheses are tested based on the same data. In the presence of data-snooping, conventional significance levels may show preliminary results with the same data unless theories are not refined. Therefore, the authors take a more critical approach in assessing significance levels by adjusting individual hypotheses. Nonetheless, the authors observe numerous calendar anomalies over 90 years of the Dow Jones Industrial Average index. The average returns are exceptionally high throughout the sample when the turn-of-the-month window from the last trading day of the month (t-1) to the third trading day of the following month (t+3). The cumulative growth rate over the four days around the month's turn is 0.473 percent, while the average growth rate is 0.0612 percent. The difference is highly statistically significant. The frequency of positive returns is also higher for the turn-of-the-month window than for a regular day. (Lakonishok & Smidt, 1988.)

Ogden (1990) studies the reasons behind the TOM effect and partially the January effect by testing the hypothesis that the concentration of cash flows at the turn of each calendar month causes these monthly irregularities in the US stock market returns. Due to this standardization, investors receive significant cash flow at the turn of the month, particularly at the turn of the year, whose reinvestments increase the return on stocks at the turn of the month. These arguments are based on Ogden's (1987) study, discovering a “preferred habitat” effect. According to the effect, a specific payoff date occurs at the turn of each calendar month, when real wages, dividends, principal and interest payments, and other liabilities are paid (Ogden, 1987). The magnitude of an increase in a month depends on the extent of the total liquid gains received during the month, and monetary policy, in turn, affects these liquid gains. Therefore, this hypothesis is related to the turn-of-the-month liquidity hypothesis. (Ogden, 1990.)

Ogden’s (1990) empirical results are consistent with Lakonishok and Smidt’s (1988) findings based on significantly high returns on the four trading days at the turn of the month. In addition, Ogden conducts regression analysis of stock index returns (CRSP Value and Equal-weighted) over the period 1969-1986, where he uses turn-of-month trading days and the Fed funds spread as explanatory variables. The turn-of-month variable represents the trading day window from last trading day of the month (-1) through the third trading day of the following month (+1, +2, +3), and the Fed funds spread is defined as the difference of the Fed funds rate median and the short-term Treasury bill rate median for a given month. Based on the regression results, the coefficient of the fed funds spread is not significant for both indices, whereas the interaction term, that is, the product of turn-of-month and fed funds spread variables, is significant and negative for both indices. This indicates that tighter monetary policy limits overall liquidity profits and increases the expected liquidity costs required to meet month-end obligations. Thus, there is an inverse relationship between stock returns on turn-of-month trading days and the stringency of monetary policy. (Ogden, 1990.)

Agrawal and Tandon (1994) extend the examination of the turn-of-the-month effect among multiple other calendar anomalies to eighteen countries other than the US. Consistent with Lakonishok and Smidt (1988), the authors note the possibility of illusions in numerous studies of calendar anomalies due to statistical errors and biases in empirical procedures. Agrawal and Tandon's (1994) research provides evidence on the nature and presence of calendar anomalies internationally since previous studies have focused on investigating anomalies in the US. Therefore, evidence from other countries offers more understanding of the underlying reasons for the anomalies observed in the US. The authors find relatively significant and significantly positive returns for the last trading day (day -1) of the month in ten of eighteen countries, similar to Lakonishok and Smidt's (1988) results for the US. The cumulative return over the four-day window around the turn of the month is significantly higher than the average four-day return in ten countries. More than 70 percent of the average monthly return in six countries is concentrated over a less than five-day period around the month's turn. Additionally, the variance of the last day of the month is very low in most countries. (Agrawal & Tandon, 1994.)

As evidence from an emerging market, Volkan, Kayacetin, and Lekpek (2016) analyze the widely recognized TOM effect in Turkish equity returns. The authors find that between 1988 and 2014, the TOM effect is strongly significant, with an average return of BIST100 index is 0.46 percent in the TOM period and 0.09 percent during the remaining days. Here, the TOM period covers the last trading day of each month and the first two trading days of the following month. In the subperiod examination, the average TOM return is 0.60 percent during 1988 – 1996, 0.56 percent during 1997-2005, 0.20 percent during 2006-2014, and highly significant in each subperiod. Although the average return is lower in the most recent subperiod, the share of the TOM period in total returns exhibits an increase from 39 percent in 1988 – 1996 to 49 percent in 1997-2005 and 86 percent in 2006-2014, indicating the amplification of TOM effect. In addition, the authors extract the conditional volatility of the index via an exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model. This way, the authors find that the change in expected volatility from the earlier month-end to the current month-end explains a statistically and economically significant share of the TOM period returns. (Volkan, Kayacetin & Lekpek, 2016.)

4.3 Day-of-the-week effect

The day-of-the-week (DOW) effect is a phenomenon in the stock markets, where the return on a particular weekday is significantly higher/lower than on other days. Initially, it has been documented that the returns on Friday are exceptionally high, and after the weekend, returns are remarkably low on Monday (Cross 1973; French 1980; Gibbons and Hess 1981). As well as the January/monthly effect and turn-of-the-month effect, commonly argued theories are based on the behavioral finance framework. For example, Thaler (1987b) argues that institutional investors and other funds may limit stock sales at the end of the week so that weekly aggregate performance indicators do not decrease. In addition, mood-related explanations suggest more optimistic investor behavior as the weekend approaches. (Thaler, 1987b).

The first well-known findings regarding the daily seasonal effect in returns have been published by Cross (1973). Cross (1973) studies the relationship and distribution of Standard and Poor's composite price changes on Mondays and Fridays. The data included a total of 844 observations on Monday and 844 on Friday. The main findings show that the index increases 62 percent of all Friday observations and 39,5 percent of all Monday observations, respectively. The average return also exhibits a higher return on Fridays than on Mondays. Moreover, Cross (1973) finds that a price increase increases in 48,8 percent of cases in the following Monday. Throughout the whole sample, a significant negative Monday effect is reported.

French (1980) examines daily returns of the Standard & Poor's composite portfolio from 1953 to 1977 and finds that the average return for Monday is significantly negative over the period and in five subperiods. French's (1980) empirical tests indicate that the information tends to be unfavorable over the weekend. For instance, if there is a threat of "panic selling" among companies as bad news occurs, companies might postpone the announcement until the weekend, allowing more time to process the information. Indeed, this kind of behavior is possible, but it does not systematically result in negative stock returns in an efficient market. Instead, investors would expect unfavorable news to be released on weekends, and throughout the week, they would discount stock prices appropriately. Even if negative Monday returns were found and this information was based on a potential investment strategy, the profits are more limited than they might appear. Based on these findings, one simple trading strategy for an individual investor would be to purchase the S&P portfolio every Monday afternoon and sell those investments on Friday afternoon, holding cash during the weekend. Excluding transaction costs, this trading strategy would have generated an average annual return of 13,4 percent from 1953 to 1977, while a simple buy and hold strategy would have yielded an annual return of 5.5 percent. However, because investors cannot avoid transaction costs, a transaction cost of 0.25 percent would have generated a lower return in each of the 24 years studied. (French, 1980.)

Gibbons and Hess (1981) find similar daily patterns in asset returns as French (1980). In addition, Monday's negative return is remarkably uniform across individual stocks. The authors conduct the empirical tests with the S&P 500 and the CRSP equal- and value-weighted portfolios. In addition, tests are also shown with actively traded individual securities of the Dow Jones Industrial Average Index to avoid the nontrading problem and determine the extent of the Monday effect across securities. According to the results, negative Monday returns appear solid and persistent on stocks and treasury bills. Even after the adjustments in the market, stock returns still show day-of-the-week effects, although these effects are not concentrated on a specific weekday. (Gibbons and Hess, 1981.)

Keim and Stambaugh (1984) examine the day-of-the-week effect on larger scale by including both large and small capitalization stocks of S&P 500 and extending the time span to 55 years from 1928 through 1982. According to the authors, negative Monday returns are consistent throughout the 55-years. In addition, the smaller the company, the more likely it is that average returns on Friday are high. Furthermore, since the NYSE was opened on Saturdays before 1952, the authors note that returns on Friday are lower when Saturday is open for trading. The return on Saturday appears to be larger than returns on other days indicating that highest return of the week occurs during the last trading day. Possible explanations of existence of such daily seasonality might be due to measurement errors. These errors refer to the hypothesis that positive errors in prices on Friday cause low Monday returns. Thus, the higher-than-mean errors on Friday tends to induce lower-than-average returns on Monday when these errors vary over time. In other words, this kind of behavior would result a lower (even negative) correlation between returns on Monday and Friday than between returns on other consecutive trading days. However, the authors document that returns between Friday and Monday are highly correlated, and thus the measurement error explanation is not consistent for explaining the weekend effect. (Keim & Stambaugh, 1984.)

Smirlock and Starks (1986) examine day-of-the-week effects using hourly values of the DJIA index over 1963 – 1983. The authors find that the dynamics of the weekend effect have changed over time. Particularly the weekend effect has "moved upwards" over time. Over the first period from 1963 to 1968, Friday close to Monday open return is positive. This return is weakened by a negative return throughout the remainder of the day, which leads to a negative return throughout the entire trading day. During the second subperiod, 1968 – 1974, weekend return is slightly negative, but the weekend effect is mainly due to significant negative returns during opening hours. Finally, in the post-1974 period, the return for the trading period on Monday is positive, although the return on opening hours is significantly negative. There is a non-trading weekend effect during this period characterized by a significant negative return from the closing price on Friday to the opening price on Monday. Thus, the authors suggest instability in the return generating process in the differences of hourly returns and their patterns across subperiods. (Smirlock & Starks, 1986.)

Connolly (1989) analyzes the robustness of the day-of-the-week and weekend effects with alternative estimation and testing approaches. The study uses daily return data of the S&P 500 index, equal-weighted CRSP index, and value-weighted CRSP index. The period for the analysis is from the first trading day in 1963 to the last trading day in 1983. The simple linear regression results show that the average Monday return is significantly negative while other days' returns are generally positive. A similar pattern emerges for the first four subsamples, and the magnitude of the negative Monday return increases. However, the results change for the 1975 – 1977 subsample, in which Monday's estimated return is positive. The negative Monday returns pattern reappears for the 1978 – 1980 and 1981 – 1983 subsamples, but the coefficient estimate is significantly different from zero only for the value-weighted index return. Additional tests by controlling for volatility clustering in daily results with a GARCH (1,1) support the evidence of weekend effect until the mid-1970s. (Connolly, 1989.)

Brooks and Persand (2001a) study the existence of the DOW-effect in five Southeast Asian stock exchanges: South Korea, Philippines, Taiwan, Thailand, and Malaysia. The authors use daily closing prices for all weekdays (Mondays to Fridays) from 31 December 1989 through 19 January 1996. The first simple linear regression model indicates that neither South Korea nor the Philippines exhibit significant calendar effects; Malaysia and Thailand show positive Monday and Tuesday effects. Wednesday effect is documented in Taiwan. Although the significant coefficients support the existence of the DOW-effect, risk factors have not been accounted for in the first estimation model. Hence, a more interactive estimation model is used to observe the variation of risk across the weekdays. This model includes market risk, which is proxied by the FTA World Price Index return. After accounting for the market risk factor, there are positive Monday effects in Thailand and Malaysia and a positive Thursday effect in Malaysia. In addition, the t-ratios decreased slightly in absolute value, indicating that the day-of-the-week effects are somewhat reduced. For Taiwan's stock market, the negative Wednesday effect completely disappears. It is also evident that average risk levels vary across weekdays. For example, the beta is 0.36 on Monday and 1.02 on Tuesday. This indicates that the movements of the Thailand stock market on Mondays are lower in relation to the movements of the general world stock market. (Brooks & Persand, 2001.)

Bhattacharya, Sarkar, and Mukhopadhyay (2003) provide evidence of the DOW effect in Indian markets. The authors assert that stock exchange regulations and the link between the banking sector and the financial market might significantly impact daily seasonality. The banking sector in India maintains a cash reserve ratio for an average of two weeks and reports to the Reserve Bank of India every other Friday, called reporting Friday. Due to this settlement process, the authors find a significant difference in the Friday returns between reporting and non-reporting weeks in the Indian stock markets. In particular, the GARCH analysis reports substantial positive returns on non-reporting Thursday and Friday, whereas the OLS procedure reports significant positive returns only on non-reporting Monday. (Bhattacharya, Sarkar, Mukhopadhyay, 2003.)

Chiah and Zhong (2019) investigate the day-of-the-week effect in 24 international stock markets, particularly how the QMJ factor is associated with the effect. The QMJ factor is the difference between the returns of quality stocks and returns of junk stocks. The QMJ factor focuses on the profitability, safety, and growth of individual stocks, and these areas are captured by selecting a raft of proxies. For instance, to measure the safety dimension, beta, idiosyncratic volatility, leverage, bankruptcy risks, and volatility of return on equity (ROE) are used as proxies. The authors present a hypothesis related to investors' mood, in which investors tend to view speculative stocks more favorably on Friday and non-speculative stocks on Monday. Thus, stocks considered high in quality coincide with long positions without speculation, whereas junk stocks involve more speculative short trading. As such, a high (low) QMJ premium is predicted on Monday (Friday). The main findings show that, globally, QMJ is significantly positive on Monday. On the contrary, the OMJ spread is globally lowest on Friday but not statistically significant. Nevertheless, the OML spread decreases monotonically from Monday to Friday, as the difference in returns is statistically significant at the 1 percent level. (Chiah & Zhong, 2019.)

4.4 Disappearance of calendar anomalies

Whether an anomaly is risk-related or behavioral, it should have a direct impact on its long-term behavior. Thus, anomalies related to behavioral characteristics should be slowly arbitraged away as investors observe them and begin to take advantage of them (Fama, 1998). However, Cochrane (1999) argues that systematic risk factors related to stock return regularity should not cause the disappearance of the regularity since these risk factors can generally be considered latent. Because the awareness of calendar anomalies has grown substantially, their importance as trading strategies has diminished.

Marquering et al. (2006) report disappearances regarding the weekend, holiday, and January due to increased data snooping and academic publications of these anomalies. Mainly, the magnitude of these anomalies decreases significantly after the first publication of a relevant academic topic. For instance, the abnormal return generated by the holiday effect dropped 77 percent after the initial publication. Thus, market participants could grow their awareness of these anomalies through academic research. (Marquering et al., 2006.)

Shanaev and Ghimire (2021) measure the magnitude of the disappearance of various stock market anomalies using the Google Scholar search algorithm based on research topics relevant to examining anomaly-exploiting trading strategies. The authors' method measures the effects of post-publication decay, scholarly attention, and data-snooping bias. As a result, the authors find that as academic attention increases, the turn-of-the-month, Monday, and January effects diminish substantially, indicating that market participants can quickly assess academic research findings by applying them to their investments. Thus, eventually, these are arbitraged away, as Fama (1998) argues. (Shanaev & Ghimire, 2021.)

5 DATA AND METHODOLOGY

This section presents the data and methodology used in this study. The data consists of the daily closing values of seven emerging market stock indices from December 30, 2004, to December 31, 2020. The data is collected from Thomson Reuters Datastream, a widely used provider of financial information. Often, calendar effects in stock markets can be easily identified using only time-series information of stock indices (Lim et al., 2010). Thus, this study uses only stock index values as data. Table 1 shows the indices used in this thesis.

Country	Stock Exchange	Index
Czech Republic	Prague Stock Exchange	Prague SE (PX)
Hungary	Budapest Stock Exchange	Budabest SE (BUX)
Malaysia	Malaysia Stock Exchange	FTSE Bursa Malaysia (KLCI)
Poland	Warsaw Stock Exchange	Warsaw SE (WIG)
South Africa	Johannesburg Stock Exchange	SA All Share Index (FTSE/JSE)
South Korea	Korea Stock Exchange	Korea SE (KOSPI)

Table 1. List of the six emerging market exchanges

The data includes three Eastern European countries, two Southeast Asian countries, and one country from Africa. All the indices are capitalization-weighted, diversified, and have a relatively long history. The anomalies tested for indices are day-of-the-week, turn-of-the-month, and the January/turn-of-the-year effect. The period used in this study shows both upward and downward fluctuations in the index values, as shown in figures 1 and 2 below. The global financial crisis and the global pandemic are shown in the figures as the value of each index declines significantly in 2008 and 2020. It can be observed the main trends are pretty similar in the emerging market indices. However, the overall change in the indices differs quite a lot since the markets have not reacted uniformly to domestic and international impulses.

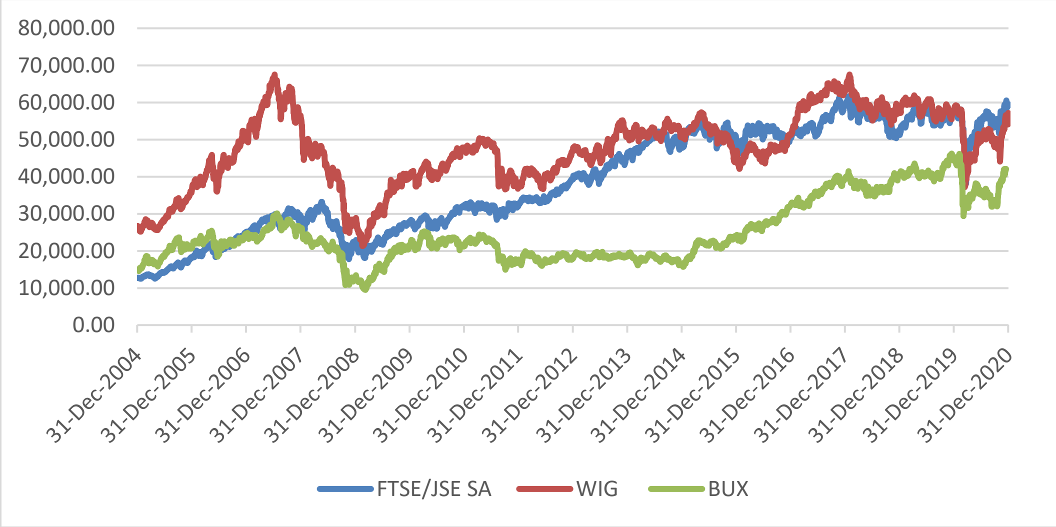

Figure 1. Price development of Johannesburg, Warsaw and Budapest stock exchanges

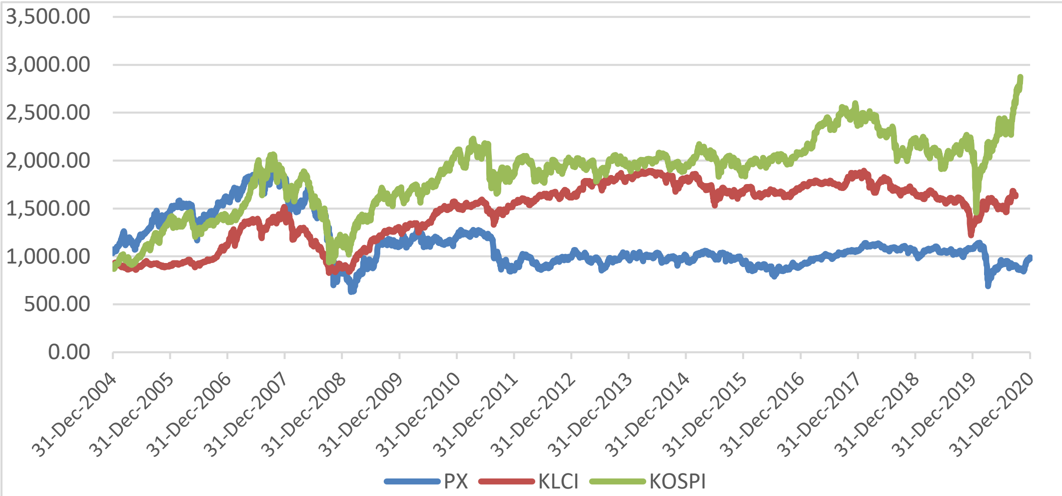

Figure 2. Price development of Prague, Malaysian and Korea stock exchanges

5.1 Methodology

The purpose of the study is to find out whether the indices under examination exhibit any day-of-the-week, turn-of-the-month, and January/turn-of-the-year effects. The model's dependent variable is the daily index return, and the seasonal dummy variables represent explanatory variables. In the study, the daily logarithmic returns are calculated for each index as follows:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where R_t represents the logarithmic return of the index at time t, P_t is the value of the index at time t and P_{t-1} is the value of the index of the previous day.

5.1.1 Linear regression models

We can economically treat seasonality with an appropriate model to include the dummy variables in the regression equations. The number of seasonal variables that could reasonably be constructed to model seasonality depends on the frequency of the data. For instance, four dummy variables would be constructed for quarterly data, twelve for monthly data, five for daily data, and so on. However, to avoid perfect multicollinearity, the constant term is not included. Alternatively, if a constant term is included, one of the dummy variables is excluded. (Brooks, 2019, p.450.)

The turn-of-the-month effect is estimates with the following simple linear regression model:

$$R_t = a_0 + \beta_1 D_{1t} + \varepsilon_t \tag{2}$$

Where R_t is the stock index return at time t, α is the constant term, β_1 is the estimated regression coefficient, D_{1t} is the dummy variable which gets value 1 at turn-of-the-month trading days and otherwise zero. The trading days included in the dummy variable are from -1 through +3, that is last four days of the month and first three days of the following month. This trading day window is proposed by Lakonishok and Smidt (1988) and it is very commonly used in analyzing TOM effects. The null hypothesis states that stock returns at the turn of the month are not different than days outside the TOM window:

$$H_0 = B_{TOM} = B_{ROM} \tag{3}$$

Where B_{TOM} denotes the coefficient of average TOM days (-1…+3) and B_{ROM} stands for the average daily returns on rest of the month. The application of the Lakonishok and Smidt (1988) method is also relevant in estimating the day-of-the-week effect. The day-of-the-week effect is tested with a simple linear regression model:

$$R_t = a_0 + \sum_{i=1}^{4} a_i D_{it} + \varepsilon_t \tag{4}$$

where R_t is the return at time t for each index examined separately, the constant term a_0 represent Monday which is the reference term against which all the other weekdays are compared to. Thus, the estimate of the constant is a_0 representing Monday, $a_0 + a_{2i}$ on Tuesday and so on. Similarly, The January/Month of the year effect is tested in a similar way using dummy variables and a constant term. The dummy variable regression model is as follows:

$$R_t = a_0 + \sum_{i=1}^{11} a_i D_{it} + \varepsilon_t \tag{5}$$

Where R_t represent the daily stock return for the index, a_0 represent the reference category for January and all the other months are average deviations from January. With this simple estimation model, the dummy variable trap is avoided.

Using the models described above, the hypotheses for the estimates are that there are no abnormal returns at each calendar month, or day of the week. Thus, there is no January effect or day-of-the-week effect, and the expected returns are almost equal for each weekday and month. Thus, the null hypothesis for can be expressed as:

$$H_0 = a_{MON} = a_{TUE} = a_{WED} = a_{THU} = a_{FRI} \tag{6}$$

Where H_0 represents the null hypothesis for day-of-the-week effect and $a_{MON\dots}a_{FRI}$ denote the the coefficient estimates for each weekday. Similarly, for the January effect, the null hypothesis states that no month of the year exhibits significantly different returns than all other months:

$$H_0 = a_{JAN} = a_{FEB} = a_{MAR} = a_{APR} = a_{MAY} = a_{JUN} = a_{JUL} = a_{AUG} = a_{SEP} = a_{OCT} = a_{NOV} = a_{DEC} \tag{7}$$

Where H_0 denotes the hypothesis for January effect and $a_{JAN}\dots a_{DEC}$ represent the coefficient estimates for each month of the year.

5.1.2 GARCH-models

The OLS (Ordinary Least Squares) model is perhaps the most common approach in detecting calendar anomalies. However, the problem with OLS-based models using daily data is that the returns have the tendency to be autocorrelated, the residuals are more likely non-normal, and standard t-tests tend to be upwardly biased (Connolly, 1989). According to Engle (1982), high-frequency data such as stock returns, interest rates, and exchange rates tend to cause an effect known as volatility clustering. This refers to a phenomenon where there is a systematic tendency for large shocks to be followed by large shocks and small shocks by small ones, indicating conditional volatility in the residuals. Therefore, Engle (1982) proposes the Lagrange multiplier test for ARCH (Autoregressive conditional heteroscedasticity) disturbances. If volatility clustering is found based on the ARCH-LM test, then an ARCH or GARCH model specification should be conducted. The following GARCH (1,1) model, which is developed by Bollerslev (1986), is used to test the turn-of-the-month, day-of-the-week, and January/monthly effects:

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + \beta_i h_{t-1} \quad \varepsilon_t \sim N(0, h_t) \tag{8}$$

In the equation above, q is the lag length for "moving average parameter" and p for autoregressive term. Because the GARCH model is used to estimate the volatility of the error term, the conditional variance h_t is not constant but depends on q lags of squared residuals. Thus, the sign of the error term ε_t is unpredictable and the variance of the error term must be non-negative and fulfill the following positivity conditions:

$$h_t > 0\colon a_0 > 0\colon a_i \geq 0, \beta_i \geq 0 \tag{9}$$

According to Bhattacharya, Sarkar, and Mukhopadhyay (2003), the main shortcomings in estimating seasonal effects arise due to possible misspecifications of the conditional mean equation. For instance, the omission of lagged returns as explanatory variables or structural breaks in the sample may cause instability in the parameters. Harvey (1995) finds that serial correlation in the stock returns of emerging markets is much higher than in developed countries. Moreover, Harvey (1995) argues that possible explanations are lack of diversification, lower market size, and trading activity. Hence, when the indices are dominated by a few stocks or specialized in a specific sector, this will generally lead to a higher serial correlation in the returns. Thus, when indices are dominated by a few stocks or specialized in a particular sector, this usually results in a higher autocorrelation in returns. Based on the evidence of high autocorrelation in the emerging market returns, the mean equation is specified with an ARIMA (p,d,q) process to mitigate possible autocorrelation in the returns.

It has been documented that the standard GARCH models have limitations because they force a symmetric volatility response into positive and negative shocks. This is because the conditional variance depends on the magnitude of the lagged residuals and not their sign. Typically, a positive shock is likely to cause less volatility than a negative shock of the same extent for stock returns. Such asymmetries are related to leverage effects, in which a company's debt to equity increases due to a fall in the company's stock price. Therefore, the shareholders of a company might consider the firm to be relatively more volatile. (Brooks, 2019, p.404.) Moreover, Harvey and Bakaert (1997) argue that standard GARCH models encounter difficulties fitting highly volatile and non-normally distributed returns due to asymmetric volatility in emerging markets. Thus, an asymmetric GARCH model is conducted in the analysis.

The exponential GARCH model, proposed by Nelson (1991), has numerous ways to express the conditional variance equation, but one possible specification is given by:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + a \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \tag{10}$$

With the comparison of the standard GARCH model, the EGARCH has several advantages. First, non-negativity constraints are not an issue since the logarithm of the variance is modeled. Furthermore, if the relationship between returns and volatility is negative, then the asymmetry term is negative, in which the EGARCH model allows asymmetric volatility. (Brooks, 2019, p.406.)

5.1.3 Descriptive statistics

Table 2 reports descriptive statistics of daily returns for every index. The mean return is highest in South Africa and lowest in the Czech Republic. Additionally, the returns in the Czech Republic are the most volatile since the daily standard deviation is the highest. When looking at the higher moment values, all the indices' daily returns are negatively skewed. This means that the probability distribution is asymmetric, and the probability of negative expected returns is higher than positive expected returns. Furthermore, the kurtosis measures the fatness of the distribution's tails and how peaked the series's mean is. Since a normal distribution is defined to have a kurtosis value equal to three, the distributions of each index return series have significant excess kurtosis.

	PX	BUX	KLCI	WIG	FTSE/JSE	KOSPI
Mean	-0.001	0.0263	0.0148	0.0190	0.0387	0.0295
Maximum	12.4	13.2	6.6	6.1	9.0	11.3
Minimum	-16.2	-12.6	-10.0	-13.5	-10.2	-11.2
Std. Dev.	0.014	0.015	0.007	0.012	0.012	0.012
Skewness	-0.66	-0.29	-0.90	-0.77	-0.33	-0.53
Kurtosis	19.68	10.88	16.93	10.26	9.15	12.32
Observations	4012	3990	3936	4002	4000	3957

Table 2. Descriptive statistics of the indices

5.1.4 Asymmetric volatility tests

Following Engle and Ng (1993), the sign and size bias test is computed jointly to determine whether an asymmetric model is required for the return series. In the presence of sign bias, positive and negative shocks have differing impacts upon conditional volatility. If there is a size bias, then the magnitude of a shock will also impact conditional volatility. Here, the test for asymmetric volatility is applied to the residuals of GARCH (1,1) model with the following regression:

$$\hat{u}_t^2 = \phi_0 + \phi_1 S_{t-1}^- + \phi_2 S_{t-1}^- \hat{u}_{t-1} + \phi_3 S_{t-1}^+ \hat{u}_{t-1} + v_t \tag{11}$$

where $\hat{u}_t^2$ represents the squared residuals of a GARCH model fitted to the returns, ϕ_0 denotes the constant term, S_{t-1}^- denotes a dummy variable taking the value 1 if $\hat{u}_{t-1} <$

0 and zero otherwise, v_t denotes an error term and S_{t-1}^{+} is defined as 1 - S_{t-1}^{-}. In the case where ϕ_1 is significant, there is a sign bias. Furthermore, if either ϕ_2 or ϕ_3 is significant, there is also a size bias (Brooks, 2019, p.406.)

As can be seen from table 3, asymmetric effects on volatility are highly significant. For instance, there is a sign bias in the South African stock exchange since the coefficient is statistically significant at the 1% level. Furthermore, there is a strong indicator of size bias for all indices except for the Malaysian stock exchange. All in all, these test results confirm that it is sensible to estimate GARCH models which allow for asymmetric volatility.

	PX	BUX	KLCI	WIG	FTSE/JSE	KOSPI
Constant	0.98	0.99	0.93	1.06	0.95	0.99
	(17.04)***	(17.21)***	(13.69)***	(16.73)***	(18.12)***	(18.12)***
Sign-Bias	0.11	-0.07	0.17	-0.03	0.22	0.05
	(1.40)	(0.00)	(1.80)*	(-0.39)	(2.98)***	(0.70)
Negative-Bias	-3.71	-7.29	-8.05	-8.92	2.90	-12.39
	(-0.95)	(-2.02)**	(-0.97)	(-1.98)**	(0.72)	(-3.10)***
Positive-Bias	-12.74	-6.28	-12.97	-19.33	-11.95	-17.56
	(-2.79)***	(-1.60)	(-1.34)	(-3.56)***	(-2.66)***	(-3.72)***

Table 3. Engle and Ng (1993) test for asymmetric volatility. T-ratios are below in parentheses. 10 %, 5 % and 1 % significance levels are denoted as *, ** and * respectively**

6 EMPIRICAL RESULTS

This chapter presents and evaluates empirical results. Firstly, visual inspection is conducted to see how the returns are clustered around each month, turn of the month, and weekday. Afterward, results regarding the regression results are presented and analyzed in more detail.

6.1 Results from linear regression model

Figure 3 shows that, on average, the highest positive returns are clustered around the turn of the month for almost every index. Clearly, very high average returns are clustered around the first day of the month and around the last three trading days of the month. In addition, some notable spikes can be seen around the middle of the month. The figure highlights the key dynamics of the anomaly; that is the amount is investments is relatively high during and around paydays.

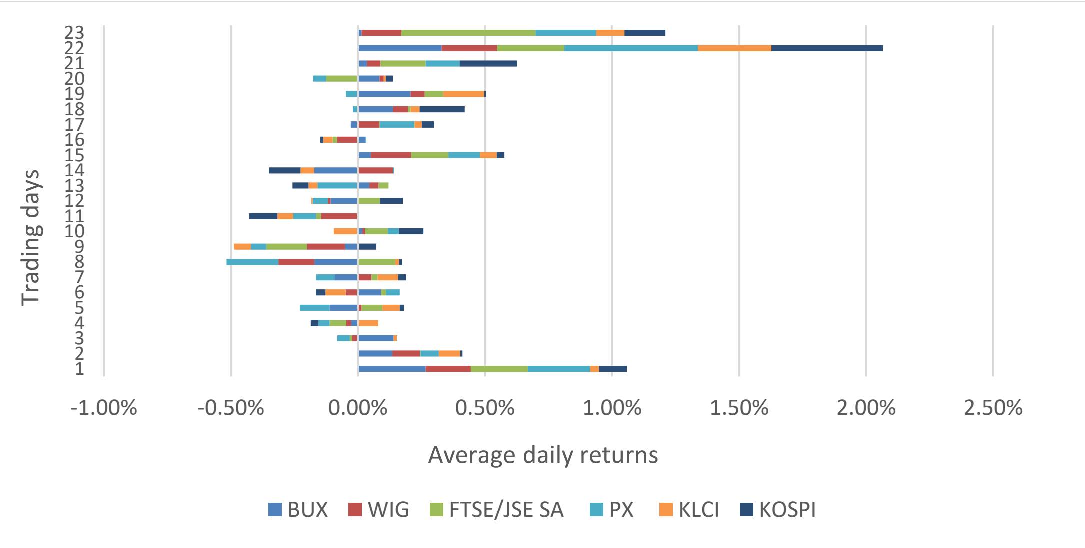

Figure 3. Average daily returns during each trading day of the month

Figure 4 shows the average daily returns in each calendar month. There are notable high average daily returns in April, July, and December. However, January returns do not appear to be very high. Consistent with the findings of Claessens et al. (1995), there is no evidence of the January effect in emerging markets. Since the positive average returns of calendar months are highly clustered during April, the tax-loss selling hypothesis does not explain the anomaly because the tax year of the countries under examination is a calendar year. It can also be observed from the figure that a significant part of the negative returns occurs between May and October, although in July, the returns are positive on average. This may indicate a known calendar anomaly called “Sell in May or go away” (Bouman and Jacobsen, 2002).

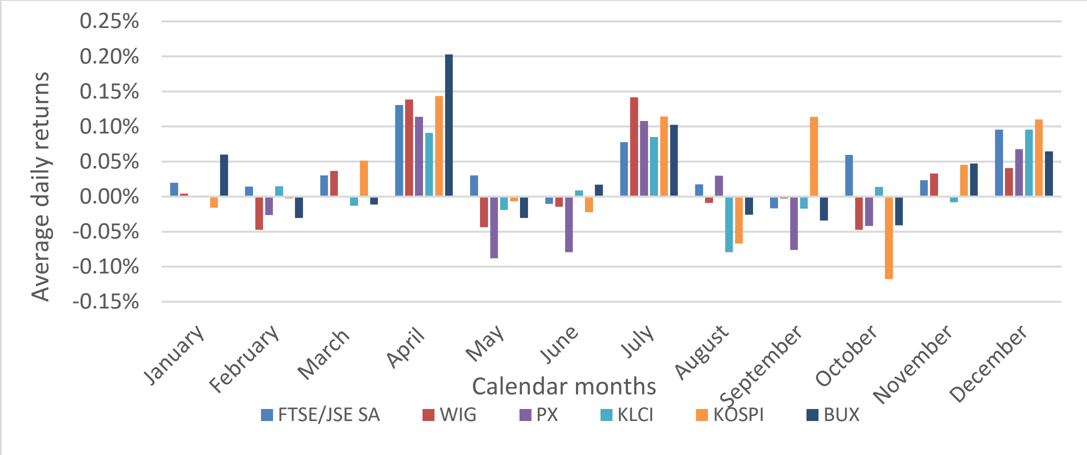

Figure 4. Average daily returns during each calendar month

Figure 3 shows the average daily returns for each day of the week for each index. There seems to be lot of deviation based on the average returns for each stock index. Regarding the well-known weekend effect, the Malaysian stock exchange exhibits high returns on Friday and low returns on Monday. In other respects, the indices under review do not appear to have significant positive or negative returns on different days of the week.

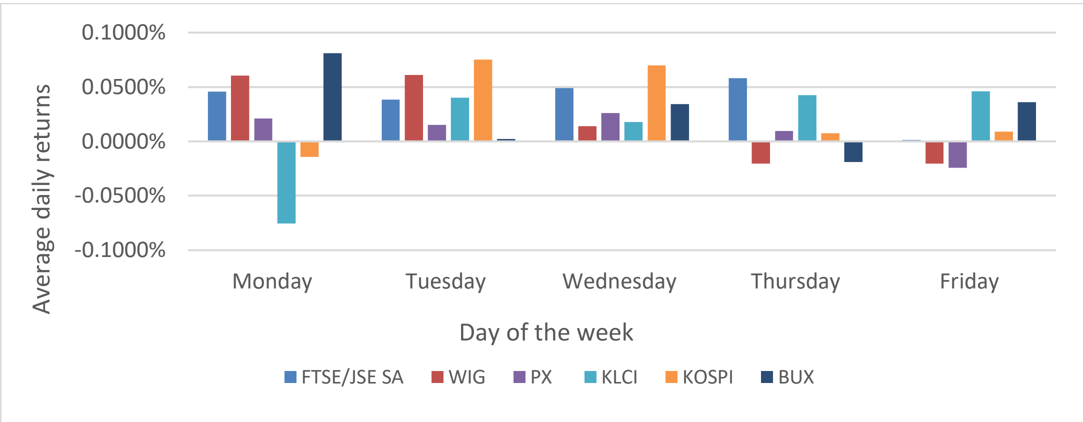

Figure 5. Average daily returns during each weekday

Based on table 4, in Prague, Budapest, Malaysian exchanges, there appears to be a statistically significant turn-of-the-month effect, at least at the 5 percent significance level. The coefficients of the turn-of-the-month (TOM) estimates are positive, indicating that, on average, the returns at the turn of the month days are significantly higher compared to trading days that are outside the TOM window. For example, the average daily return of the Prague Exchange is 0.15 percent in the TOM window, and apart from the TOM window, the average daily return is -0.03 percent.

Variable	PX	BUX	KCLI	WIG	FTSE/JSE SA	KOSPI
TOM (%)	0.15	0.18	0.06	0.08	0.03	0.05
	(2.74) ***	(2.97) ***	(2.02) **	(-1.56)	(-0.81)	(-0.98)
Constant (%)	-0.03	-0.01	0.00	0.00	0.04	0.02
	(-1.20)	(-0.32)	(-0.22)	(-0.19)	(-1.42)	(-0.90)

Table 4. OLS regression results of the turn-of-the-month effect. Coefficients are reported in each cell as percentages and the t-ratios are below in parentheses. 10 %, 5 % and 1 % significance levels are denoted as *, ** and * respectively**

Table 5 reports the OLS regression results of the day-of-the-week effect. The day-of-the-week effect occurs only in the Malaysian exchange because the average deviations of the Monday and other days of the week are positive and statistically significant at the 1 percent level. The average Monday return is negative and statistically significant. Thus, on Mondays, investors are more likely to sell their stocks at the Malaysian exchange and buy them on the rest of the weekdays.

Variable	PX	BUX	KCLI	WIG	FTSE/JSE SA	KOSPI
C	0.02 (0.44)	0.08 (1.47)	-0.08 (-2.79) ***	0.06 (1.37)	0.05 (1.30)	-0.01 (-0.32)
Tue	-0.05 (-0.80)	-0.08 (-1.02)	0.12 (3.05) ***	0.00 (0.01)	-0.01 (-0.12)	0.09 (1.42)
Wed	0.00 (0.07)	-0.05 (-0.61)	0.09 (2.47) **	-0.05 (-0.75)	0.00 (0.05)	0.08 (1.34)
Thu	-0.01 (-0.17)	-0.10 (-1.30)	0.12 (3.12) ***	-0.08 (-1.30)	0.01 (0.20)	0.02 (0.35)
Fri	-0.05 (-0.66)	-0.05 (-0.58)	0.12 (3.21) ***	-0.08 (-1.29)	-0.04 (-0.71)	0.02 (0.37)
F-stat	0.31	0.49	3.64***	0.85	0.25	0.83

Table 5. OLS regression results of the day-of-the-week effect. Coefficients are reported in each cell as percentages and the t-ratios are below in parentheses. 10 %, 5 % and 1 % significance levels are denoted as *, ** and * respectively.**

Table 6 reports the OLS regression results regarding the January effect and monthly seasonality in the indices. As can be seen, none of the indices report any monthly effects because none of the coefficients are statistically significant. Moreover, based on the F-statistic, there are no significant differences in the mean returns between each month. This indicates that the January/monthly effects have disappeared in the emerging markets, and April's returns are not statistically significant either, although visual inspection exhibits relatively high returns in April.

Variable	PX	BUX	KCLI	WIG	FTSE/JSE SA	KOSPI
C	0.00 (0.01)	0.06 (0.73)	-0.02 (-0.23)	0.00 (0.06)	0.02 (0.29)	-0.02 (-0.23)
FEB	-0.03 (-0.26)	-0.09 (-0.77)	0.01 (0.13)	-0.05 (-0.53)	-0.01 (-0.06)	0.01 (0.13)
MAR	0.00 (-0.02)	-0.07 (-0.61)	0.07 (0.70)	0.03 (0.34)	0.01 (0.11)	0.07 (0.70)
APR	0.11 (1.08)	0.14 (1.20)	0.16 (1.65)	0.13 (1.38)	0.11 (1.14)	0.16 (1.65)
MAY	-0.09 (-0.85)	-0.09 (-0.77)	0.01 (0.09)	-0.05 (-0.49)	0.01 (0.11)	0.01 (0.09)
JUN	-0.08 (-0.78)	-0.04 (-0.37)	-0.01 (-0.07)	-0.02 (-0.19)	-0.03 (-0.32)	-0.01 (-0.07)
JUL	0.11 (1.03)	0.04 (0.36)	0.13 (1.36)	0.14 (1.45)	0.06 (0.62)	0.13 (1.36)
AUG	0.03 (0.28)	-0.09 (-0.73)	-0.05 (-0.53)	-0.01 (-0.14)	0.00 (-0.02)	-0.05 (-0.53)
SEP	-0.08 (-0.74)	-0.09 (-0.81)	0.13 (1.32)	-0.01 (-0.07)	-0.04 (-0.38)	0.13 (1.32)
OCT	-0.04 (-0.41)	-0.10 (-0.86)	-0.10 (-1.05)	-0.05 (-0.54)	0.04 (0.42)	-0.10 (-1.05)
NOV	0.00 (-0.01)	-0.01 (-0.11)	0.06 (0.64)	0.03 (0.30)	0.00 (0.04)	0.06 (0.64)
DEC	0.07 (0.63)	0.00 (0.04)	0.13 (1.29)	0.04 (0.37)	0.08 (0.78)	0.13 (1.29)
F-stat	0.85	0.75	1.40	0.90	0.40	1.40

Table 6. OLS regression results of the January/monthly effect. Coefficients are reported in each cell as percentages and the t-ratios are below in parentheses. 10 %, 5 % and 1 % significance levels are denoted as *, ** and * respectively.**

Based on the results of OLS regression models, the most observed calendar effect is the turn-of-the-month effect. In addition, only in the Malaysian exchange, significant seasonality in the average weekday returns have been found. The January effect or any monthly effects are not present in any of the indices. As noted early, numerous studies have shown that the January effect/monthly effects have existed, and particularly among small capitalization indices, but they have disappeared during the 21st century. Since this thesis focus on large capitalization-weighted indices, it confirms that monthly seasonality is unlikely to exist. However, since the OLS models are based purely on the average differences in the daily returns, and the time-varying volatility of the models has not been considered, the anomalies are re-estimated with GARCH models, including autoregressive and or moving average terms.

6.2 Standard GARCH (1,1) model -results

Table 7 presents the results for the turn-of-the-month effect with GARCH (1,1) specification. The turn-of-the-month effect is highly significant at the 1 percent level for Prague and Budapest exchanges. Additionally, the turn-of-the-month effect is still statistically significant at the 5 percent level in the Malaysian exchange.

Based on the residual diagnostics, the GARCH (1,1) eradicates serial correlation in the residuals up to 20 lags apart from the Prague exchange, where the second lag of Ljung Box Q-statistic is statistically significant at 5 percent level. Thus, the model fails to account for the serial dependence in the residuals. The autocorrelation issue is still present when testing the model after including several autoregressive and/or moving average terms. Furthermore, the ARCH-LM test indicates no remaining heteroscedasticity in the residuals apart from the Warsaw stock exchange. This means that volatility clustering is still present, and therefore the model is not well-specified for the Warsaw exchange.

The variance equation's coefficients on both the lagged squared (ARCH) residual and lagged conditional variance (GARCH) terms are highly statistically significant. Also, the constant term is statistically significant. In addition, as is typical of GARCH model estimates for stock returns, the sum of the coefficients in terms of the ARCH and GARCH is very close to one. This implies that shocks to the conditional variance will be highly persistent. This indicates that past volatility helps to predict future volatility.

Variable	PX	BUX	KCLI	WIG	FTSE/JSE SA	KOSPI
Mean equation						
C	0.02 (1.25)	0.04 (1.77)	0.01 (1.34)	0.03 (1.51)	0.05 (1.19)	0.05 (1.09)
TOM	0.11 (3.22)***	0.14 (3.07)***	0.05 (1.97)**	0.07 (1.66)*	0.07 (1.34)	-0.03 (-0.80)
AR(1)			10.24 (5.68)***			
MA(1)	1.96 (1.11)	4.07 (2.39)**		7.34 (4.33)***		
MA(2)						
Variance equation						
Constant	2.53E-06 (5.04)***	4.2E-06 (4.37)***	8.32E-07 (4.58)***	2.01E-06 (4.26)***	2.14E-06 (5.30)***	1.7E-06 (6.67)***
ARCH(-1)	0.145 (8.70)***	0.104 (7.27)***	0.112 (6.70)***	0.072 (5.96)***	0.099 (12.00)***	0.083 (13.45)***
GARCH(-1)	0.845 (58.77)***	0.878 (60.64)***	0.877 (63.51)***	0.914 (75.22)***	0.887 (93.36)***	0.905 (139.25)***
Residual diagnostics						
Log likelihood	12700.13	11710.19	14413.40	12440.59	12611.45	12536.98
ARCH (F-stat) 5 lags	0.48	0.50	0.44	2.47**	1.38	1.71
ARCH (Prob) 5 lags	0.79	0.78	0.82	0.03	0.23	0.13
LQB (1)	3.83	0.40	0.46	0.88	1.53	0.85
LQB (2)	3.87**	1.91	0.46	1.87	1.53	2.92
LQB (3)	4.40*	2.94	1.51	2.86	2.30	3.73
LQB (4)	6.29	4.96	2.91	3.34	2.31	4.35
LQB (5)	7.18	5.11	4.77	3.70	3.12	5.81

Table 7. GARCH (1,1) regression results of the turn-of-the-month effect. Coefficients are reported in each cell as percentages and the z-ratios are below in parentheses. 10 %, 5 % and 1 % significance levels are denoted as *, ** and * respectively.**

Table 8 reports the GARCH (1,1) regression results for the day-of-the-week effect. The sum of the ARCH and GARCH terms is very close to one, suggesting highly persistent volatility. For the Prague, Warsaw, and Johannesburg exchanges, the dummy variables of Monday are positive and statistically significant. Moreover, for the Malaysian and Korean exchanges, the coefficient for Tuesday is positive and statistically significant. This means that the difference between the average Tuesday and average Monday is significantly high, indicating a positive Tuesday effect. Furthermore, the positive Friday effect remains in the Malaysian exchange since the average return difference between Monday and Friday is statistically significant at the 5 percent level. Thus, after including the AR(1) term, the negative Monday effect disappears due to the serial dependence structure in the daily return series.

Moreover, the highly effective ARCH term indicates that the returns on the previous day influence returns on a particular day. The residual diagnostics show autocorrelation in the Prague exchange, although the significance level of the Q-statistic in lag 2 is now significant at the 10 percent level. Even though the inclusion of seasonal dummy variables might reduce the serial dependence in the residuals, the Q-statistic shows significant autocorrelation at the 1 percent level from the ninth lag onwards. Other indices, on the other hand, do not exhibit any autocorrelation up to 20 lags. In addition, no significant ARCH effect is detected apart for the Warsaw stock exchange. The Korean exchange also displays heteroscedasticity since the ARCH test's F-stat is statistically significant at the 10 percent level. Thus, the autocorrelation and heteroscedasticity issues regarding Prague, Warsaw and Korean exchanges indicates the inadequacy of the GARCH (1,1) model.

Variable	PX	BUX	KCLI	WIG	FTSE/JSE SA	KOSPI
Mean equation						
C	0.06 (2.06)**	0.05 (1.21)	-0.01 (-0.51)	0.10 (2.84)***	0.12 (3.78)***	0.00 (-0.07)
TUE	-0.08 (-1.71)*	-0.05 (-0.85)	0.05 (2.03)**	-0.06 (-1.32)	-0.10 (-2.20)**	0.11 (2.38)**
WED	0.02 (0.10)	0.08 (1.30)	0.03 (1.19)	-0.07 (-1.30)	-0.07 (-1.44)	0.07 (1.49)
THU	-0.03 (-0.80)	0.01 (0.18)	0.03 (1.20)	-0.09 (-1.70)	-0.05 (-1.17)	0.06 (1.38)
FRI	0.00 (-0.02)	0.02 (0.35)	0.05 (2.22)**	-0.09 (1.87)*	-0.08 (-1.67)*	0.06 (0.26)
AR(1)			10.48 (6.09)***			
MA(1)	2.28 (1.29)	4.41 (2.59)**		7.54 (4.43)***		
MA(2)					-3.31 (-2.05)**	
Variance equation						
Constant	2.6E-06 (4.97)***	4.2E-06 (4.41)***	8.5E-07 (7.32)***	2.0E-06 (4.26)***	2.1E-06 (5.33)***	1.7E-06 (6.52)***
ARCH(-1)	0.145 (8.67)***	0.104 (7.29)***	0.113 (17.51)***	0.072 (5.94)***	0.099 (12.02)***	0.084 (13.41)***
GARCH(-1)	0.845 (58.87)***	0.877 (60.56)***	0.876 (118.66)***	0.915 (75.88)***	0.887 (93.58)***	0.904 (137.14)***
Residual diagnostics						
Log likelihood	12697.60	11708.13	14413.67	12441.17	12612.21	12540.66
ARCH (F-stat) 5 lags	0.50	0.51	0.46	2.52**	1.31	1.91*
ARCH (Prob) 5 lags	0.78	0.77	0.81	0.03	0.25	0.09
LQB (1)	3.68	0.34	0.44	0.78	1.79	0.86
LQB (2)	3.74*	1.81	0.44	1.69	1.79	3.07
LQB (3)	4.17	2.72	1.41	2.62	2.47	4.07
LQB (4)	6.03	4.94	3.02	3.06	2.47	4.70
LQB (5)	6.60	5.29	5.02	3.35	3.46	6.21

Table 8. GARCH (1,1) regression results of the day-of-the-week effect. Coefficients are reported in each cell as percentages and the z-ratios are below in parentheses. 10 %, 5 % and 1 % significance levels are denoted as *, ** and * respectively.**

Table 9 reports the GARCH (1,1) results for the January/monthly effect. The results report significantly positive returns in January and negative for the Prague stock exchange in May and June. Therefore, after accounting for volatility clustering, there is a January effect in the Prague stock exchange. However, due to the significant autocorrelation in the residuals, the results are inadequate. None of the remaining indices exhibit any January/monthly effects in the returns.

Variable	PX	BUX	KCLI	WIG	FTSE/JSE SA	KOSPI
Mean equation						
C	0.10 (2.43)**	0.10 (1.77)*	0.01 (0.23)	0.08 (1.50)	0.07 (1.66)*	0.01 (0.33)
Feb	-0.05 (-0.70)	-0.11 (-1.43)	0.05 (1.10)	-0.07 (-0.87)	0.00 (0.08)	0.04 (0.63)
Mar	-0.08 (-1.26)	-0.05 (-0.52)	0.03 (0.56)	-0.04 (-0.48)	-0.04 (-0.60)	0.05 (0.76)
Apr	-0.06 (-0.89)	0.06 (0.63)	0.03 (0.69)	-0.02 (-0.23)	0.03 (0.38)	0.07 (1.13)
May	-0.14 (-2.13)**	-0.03 (-0.35)	-0.01 (-0.18)	-0.11 (-1.40)	-0.07 (-1.16)	0.01 (0.08)
Jun	-0.16 (-2.41)**	-0.12 (-1.32)	0.01 (0.26)	-0.11 (-1.30)	-0.07 (-1.01)	-0.02 (-0.25)
Jul	0.02 (0.37)	-0.05 (-0.49)	0.05 (1.02)	0.02 (0.23)	0.05 (0.77)	0.07 (1.16)
Aug	-0.07 (-1.23)	-0.06 (-0.75)	-0.01 (-0.13)	-0.04 (-0.50)	-0.05 (-0.79)	-0.04 (-0.61)
Sep	-0.07 (-1.14)	-0.07 (-0.80)	-0.02 (-0.36)	-0.02 (-0.22)	-0.03 (-0.42)	0.10 (1.50)
Oct	-0.05 (-0.68)	-0.01 (-0.16)	0.04 (0.75)	-0.06 (-0.81)	0.06 (0.87)	-0.03 (-0.44)
Nov	-0.10 (-1.48)	-0.05 (-0.58)	-0.07 (1.45)	-0.06 (-0.80)	-0.04 (-0.72)	0.03 (0.46)
Dec	-0.02 (-0.35)	0.00 (0.02)	0.08 (1.77)	-0.01 (-0.12)	0.06 (0.88)	0.09 (1.31)
AR(1)		-	10 (5.62)***	-	-	-
MA(1)	1.68 (1.96)**	4.0 (2.34)**		7.3 (4.29)***	-	-
MA(2)					-3.6 (-2.22)**	-
Variance equation						
Constant	2.6E-06 (5.02)***	4.1E-06 (6.77)***	8.4E-07 (6.89)***	2.0E-06 (4.25)***	2.2E-06 (5.37)***	1.7E-06 (6.64)***
ARCH(-1)	0.146 (8.71)***	0.103 (14.02)***	0.114 (16.63)***	0.072 (5.96)***	0.100 (11.86)***	0.083 (13.36)***
GARCH(-1)	0.844 (58.42)***	0.879 (102.03)***	0.875 (111.92)***	0.915 (75.72)***	0.885 (91.20)***	0.905 (138.85)***
Residual diagnostics						
Log likelihood	12701.75	11708.48	14418.66	12441.72	12615.41	12541.70
ARCH (F-stat) 5 lags	0.45	0.48	0.38	2.43**	1.25	1.70
ARCH (Prob) 5 lags	0.81	0.79	0.86	0.03	0.28	0.13
LQB (1)	3.80	0.36	0.41	0.84	1.26	0.79
LQB (2)	3.80*	2.07	0.43	1.90	1.26	2.44
LQB (3)	4.00	3.25	1.37	2.75	1.69	3.02
LQB (4)	5.11	5.08	2.54	3.19	1.71	3.86
LQB (5)	5.61	5.40	4.76	3.48	2.78	5.68

Table 9. GARCH (1,1) regression results of the January/monthly effect. Coefficients are reported in each cell as percentages and the z-ratios are below in parentheses. 10 %, 5 % and 1 % significance levels are denoted as *, ** and * respectively.**

6.3 EGARCH (1,1) -results

Table 10 reports the EGARCH regression regarding the turn-of-the-month effect. The turn-of-the-month variable for Prague, Budapest, and Malaysian Exchanges remains statistically significant. Additionally, no significant autocorrelation is detected based on the Ljung-Box Q-statistic at any lags, and no significant heteroscedasticity remains, except for the Warsaw stock exchange. The GARCH term is very close to unity and highly statistically significant for every index, meaning that the conditional volatility is highly persistent. Since the asymmetry term is negative and statistically significant, it corresponds to bad news increasing volatility more than the good news of the same magnitude. This suggest that there is a clear leverage effect for every stock index returns.

Variable	PX	BUX	KCLI	WIG	FTSE/JSE SA	KOSPI
Mean equation						
C	0.00 (0.28)	0.00 (-0.04)	0.00 (0.12)	0.01 (0.79)	0.02 (1.02)	0.02 (1.37)
TOM	0.11 (3.30)***	0.15 (3.22)***	0.05 (2.57)**	0.04 (0.93)	0.05 (1.51)	-0.02 (-0.75)
AR(1)			10.71 (6.55)			
MA(1)	3.17 (1.82)*	4.24 (2.54)**		8.33 (5.05)***		
MA(2)						
Variance equation						
Constant	-0.455 (-8.37)***	-0.365 (-6.94)***	-0.345 (-6.16)***	-0.271 (-6.61)***	-0.274 (-9.74)***	-0.304 (-12.01)***
ARCH(-1)	0.259 (10.49)***	0.200 (8.18)***	0.196 (8.32)***	0.140 (7.12)***	0.131 (11.42)***	0.158 (14.91)***
Asymmetry	-0.076 (-4.05)***	-0.062 (-3.68)***	-0.069 (-4.51)***	-0.065 (-5.17)***	-0.109 (-15.55)***	-0.079 (-11.41)***
GARCH(-1)	0.972 (190.15)***	0.976 (194.45)***	0.981 (206.86)***	0.982 (264.86)***	0.981 (373.86)***	0.980 (416.72)***
Residual diagnostics						
Log likelihood	12725.02	11724.09	14436.62	12466.46	12669.92	12579.97
ARCH (F-stat) 5 lags	0.73	1.13	1.07	2.14*	1.53	1.40
ARCH (Prob) 5 lags	0.60	0.34	0.37	0.06	0.18	0.22
LQB (1)	1.64	0.30	0.19	0.01	1.49	0.62
LQB (2)	1.64	1.81	0.37	1.43	1.53	2.41
LQB (3)	2.48	2.60	0.91	1.91	2.09	3.02
LQB (4)	4.49	4.38	2.24	2.22	2.09	3.73
LQB (5)	5.72	4.52	4.25	2.43	3.13	4.67

Table 10. EGARCH regression results of the turn-of-the-month effect. Coefficients are reported in each cell as percentages and the z-ratios are below in parentheses. 10 %, 5 % and 1 % significance levels are denoted as *, ** and * respectively.**

Table 11 reports EGARCH regression results for the day-of-the-week effect. The Prague Stock Exchange does not exhibit a positive Monday effect as asymmetry disturbances are captured. However, the difference between the Monday and Tuesday average return is statistically significant and negative, indicating a negative Tuesday effect. Otherwise, the results in the mean equation are like those of the standard GARCH (1,1) model. The variance equation exhibits persistent conditional volatility and significant asymmetry in the shocks. Thus, bad news on a particular day of the week has a more substantial impact on volatility than good news. Apart from the Warsaw stock exchange, no significant autocorrelation and heteroscedasticity remain.

Index	PX	BUX	KCLI	WIG	FTSE/JSE SA	KOSPI
Mean equation						
C	0.04 (1.46)	0.02 (0.48)	-0.02 (-1.05)	0.08 (2.35)**	0.08 (2.65)***	-0.03 (-0.95)
TUE	-0.09 (-2.15)**	-0.08 (1.30)	0.05 (1.98)**	-0.05 (-1.01)	-0.10 (-2.22)**	0.10 (2.48)**
WED	-0.01 (0.24)	0.08 (1.33)	0.02 (1.01)	-0.07 (-1.47)	-0.07 (-1.61)	0.07 (1.57)
THU	-0.04 (-1.05)	0.00 (0.01)	0.03 (1.06)	-0.09 (-1.79)*	-0.05 (-1.11)	0.06 (1.37)
FRI	0.00 (0.04)	0.01 (0.25)	0.04 (2.00)**	-0.09 (-1.85)*	-0.07 (-1.54)	0.01 (0.20)
AR(1)	4.09 (2.38)**	4.32 (2.55)**		8.41 (5.10)***		
MA(1)					-3.57 (-2.23)	
MA(2)						
Variance equation						
Constant	-0.450 (-8.35)***	-0.365 (-6.96)***	-0.349 (-12.56)***	-0.271 (-6.63)***	-0.278 (-9.81)***	-0.305 (-6.86)***
ARCH(-1)	0.257 (10.29)***	0.200 (8.10)***	0.198 (18.18)***	0.140 (7.07)***	0.131 (11.49)***	0.160 (7.69)***
Asymmetry	-0.078 (-4.04)***	-0.064 (-3.82)***	-0.069 (-10.42)***	-0.065 (-5.20)***	-0.110 (-15.37)***	-0.079 (-6.61)***
GARCH(-1)	0.972 (191.10)***	0.976 (195.77)***	0.980 (422.19)***	0.982 (265.58)***	0.981 (371.31)***	0.980 (252.60)***
Residual diagnostics						
Log likelihood	12723.10	11723.29	14437.05	12468.52	12671.37	12583.61
ARCH (F-stat) 5 lags	0.71	1.14	1.07	2.21**	1.46	1.64
ARCH (Prob) 5 lags	0.62	0.34	0.38	0.05	0.20	0.15
LQB (1)	0.88	0.45	0.05	0.01	1.84	0.71
LQB (2)	0.88	2.02	0.26	1.32	1.87	2.65
LQB (3)	1.56	2.72	0.70	1.77	2.38	3.44
LQB (4)	3.44	4.75	2.17	2.08	2.38	4.16
LQB (5)	4.25	5.07	4.30	2.23	3.60	5.12

Table 11. EGARCH regression results of the day-of-the-week effect. Coefficients are reported in each cell as percentages and the z-ratios are below in parentheses. 10 %, 5 % and 1 % significance levels are denoted as *, ** and * respectively**

As can be seen from Table 12, the January/monthly effect results have not changed after estimating the model with EGARCH specifications. The Prague Stock Exchange still exhibits a significantly positive January effect. The differences between June, May, and November average returns and mean January returns are significant at the 1 percent significance level. This suggests that once the asymmetry in volatility has been captured, the index exhibits significantly negative May, June, and November effects. The residual diagnostics report no serial correlation in the residuals. Moreover, heteroscedasticity is significant at the 10 percent level in the Warsaw exchange.

Variable	PX	BUX	KCLI	WIG	FTSE/JSE SA	KOSPI
Mean equation						
C	0.09 (2.19)**	0.08 (1.52)	0.03 (0.61)	0.09 (1.50)	0.03 (0.84)	0.00 (0.11)
Feb	-0.03 (-0.41)	-0.08 (-0.81)	0.01 (0.11)	-0.01 (-0.10)	0.02 (0.27)	0.01 (0.17)
Mar	-0.08 (-1.49)	-0.13 (-1.45)	-0.02 (-0.30)	-0.11 (-1.32)	-0.05 (-0.99)	0.00 (0.05)
Apr	-0.06 (-1.00)	0.08 (0.92)	0.01 (0.24)	-0.05 (-0.66)	0.05 (0.96)	0.08 (1.46)
May	-0.18 (-3.04)***	-0.05 (-0.62)	-0.04 (-0.70)	-0.12 (-1.46)	-0.05 (-0.93)	0.01 (0.14)
Jun	-0.17 (-2.67)***	-0.14 (-1.77)*	-0.06 (-1.07)	-0.14 (-1.84)*	-0.07 (-1.28)	-0.02 (-0.38)
Jul	0.01 (0.22)	-0.06 (-0.87)	0.01 (0.20)	0.02 (0.27)	0.03 (0.51)	0.07 (1.11)
Aug	-0.06 (-1.16)	-0.07 (-0.89)	-0.03 (-0.50)	-0.05 (-0.56)	-0.02 (-0.37)	-0.06 (-0.98)
Sep	-0.08 (-1.33)	-0.12 (-1.57)	-0.10 (-1.69)*	-0.08 (-1.06)	-0.05 (-0.85)	0.08 (1.33)
Oct	-0.04 (-0.65)	-0.01 (-0.18)	0.00 (-0.02)	-0.09 (-1.22)	0.04 (0.61)	-0.05 (-0.73)
Nov	-0.14 (-2.32)**	-0.08 (-1.03)	-0.09 (-1.57)	-0.14 (-1.73)	-0.04 (-0.73)	-0.01 (0.76)
Dec	-0.02 (-0.30)	-0.03 (-0.37)	0.07 (1.27)	-0.03 (1.27)	0.04 (0.76)	0.04 (0.64)
AR(1)			10.2 (5.87)***			
MA(1)	3.30 (2.09)**	3.8 (2.27)**		8.16 (4.92)***		
MA(2)					-3.8 (-2.38)**	
Variance equation						
Constant	-0.454 (-8.40)***	-0.356 (-6.91)***	-0.341 (-6.30)***	-0.264 (-6.82)***	-0.273 (-9.50)***	-0.302 (-11.77)***
ARCH(-1)	0.260 (10.46)***	0.197 (8.17)***	0.193 (8.17)***	0.138 (7.41)***	0.130 (11.07)***	0.157 (14.72)***
Asymmetry	-0.079 (-4.16)***	-0.063 (-3.76)***	-0.078 (-3.76)***	-0.069 (-5.55)***	-0.110 (-15.13)***	-0.081 (-11.43)***
GARCH(-1)	0.972 (191.15)***	0.976 (191.15)***	0.981 (199.56)***	0.982 (277.73)***	0.981 (370.28)***	0.979 (411.28)***
Residual diagnostics						
Log likelihood	12730.55	11723.9	14446.21	12472	12674.56	12584.8
ARCH F-stat	0.61	1.08	0.96	2.04*	1.51	1.32
ARCH (Prob)	0.69	0.36	0.44	0.06	0.18	0.25
LQB (1)	1.01	0.53	0.37	0.02	1.35	0.49
LQB (2)	1.14	2.23	0.46	1.33	1.35	1.71
LQB (3)	1.48	3.18	1.04	1.72	1.64	2.11
LQB (4)	2.51	4.79	2.23	2.02	1.71	3.14
LQB (5)	3.16	5.09	4.57	2.24	3.09	4.37

Table 12. EGARCH regression results of the January/monthly effect. Coefficients are reported in each cell as percentages and the z-ratios are below in parentheses. 10 %, 5 % and 1 % significance levels are denoted as *, ** and * respectively.**

In summary to the GARCH (1,1) models, a significant turn-of-the-month effect exists in the Prague, Budapest, and Malaysian Exchanges. Furthermore, a significant positive Monday effect is present in the Prague Stock Exchange, Warsaw Stock Exchange, and Johannesburg Stock Exchange. Additionally, a positive Tuesday and Friday effect occurs in the Malaysian Exchange. By contrast, the Johannesburg Exchange exhibits a negative Tuesday effect while the Korea Exchange exhibits a positive Tuesday effect. Significant autocorrelation remains in Prague Exchange, and there is considerable heteroskedasticity in the Warsaw exchange. In all other indices, no significant autocorrelation and heteroscedasticity remain.

Moreover, a well-specified model should have normally distributed standardized residuals. The variance specifications do not fulfill the normality target because there is still excess kurtosis and negative skewness. Therefore, all three calendar anomalies are estimated with the EGARCH model. The results are consistent with the standard GARCH (1,1) model since the significant turn-of-the-month, day-of-the-week, January/monthly effects remain after capturing asymmetries in volatility. Only the positive Monday effect in the Prague exchange has disappeared, and the return on Tuesday is negative and significant. Since the log-likelihood is more remarkable for every index in the EGARCH model, it accounts for the dynamics of volatility to a greater extent than the standard GARCH model. Furthermore, the EGARCH model is better in eradicating autocorrelation in the residuals of Prague exchange returns. However, significant heteroskedasticity remains in the Warsaw exchange when testing the turn-of-the-month and day-of-the-week effects.

7 CONCLUSIONS

This thesis examines the existence of three well-known calendar anomalies in six emerging market stock exchanges. The three calendar anomalies under examination are the January/monthly, turn-of-the-month, and day-of-the-week. The sample period was taken from January 2005 through December 2020, covering significant economic shocks and a steady period of market upturn. The anomalies under examination are tested with four different models to find as adequate results as possible. Because modeling calendar anomalies commonly involves only daily stock returns and seasonal dummy variables, it is crucial to conduct different estimation techniques to explain several essential features of financial data, especially volatility dynamics. This provides investors with information about the time-varying risks associated with calendar anomalies.

OLS regression results show the turn-of-the-month effect in Prague, Budapest, and Malaysian stock exchanges. The reasons for the significant-high returns at the end of the month may be due to the regular payment dates in these countries, where investors receive salaries, dividends, and interest payments at month-ends and invest these in stocks (Ogden, 1990). Since the cash flows of many investment funds increase towards the end of the month because of the monthly income received by investors, the improved liquidity position causes relatively high demand for many securities. (Ritter, 1988, Ziemba, 1989). The day-of-the-week effect is strongly found in the Malyasian exchange, in which significantly low returns occur on Monday and significantly high returns on Friday. This might indicate a lower investor mood at the beginning of the week than at the end of the week. This study finds no January/monthly effects based on the OLS regression results.

After running the OLS regressions, the data generating process is reviewed with diagnostic tests to identify possible autocorrelation, heteroscedasticity, and non-normality in the residuals. Based on the diagnostic test results, volatility clustering and autocorrelation is strongly observed, and therefore all three calendar anomalies are estimated with GARCH (1,1) models. In addition, since the asymmetric volatility tests report sign and size biases and the residuals exhibit significant non-normality, the regressions are estimated with the EGARCH model.

The outcomes from the GARCH models show that shocks to conditional volatility will be highly persistent. The asymmetric GARCH models indicate significant leverage effects in the conditional volatility, meaning that bad news results in greater volatility than the good news of the same magnitude. The standard GARCH (1,1) model implies a positive January effect and negative May and June effects in the Prague exchange. The GARCH models show that turn-of-the-month effect is still significant in Prague, Budapest, and Malaysian stock exchanges. In addition, significantly positive Monday returns occur in Prague, Warsaw, and Johannesburg stock exchanges. Correspondingly, a negative Tuesday effect is found in the Johannesburg stock exchange and positive Tuesday effects in the Korean and Malaysian stock exchanges. The positive Friday effect remains in the Malaysian stock exchange. The EGARCH model shows positive January and May, June, November effects in the Prague exchange. The turn-of-the-month effect is still significant in Prague, Budapest, and Malaysian exchanges. The positive Monday effect in the Prague exchange has disappeared, but there is still a negative Tuesday effect.

Since there is a great amount of variation in the results of different estimation models, no clear generalization can be made of the existence of the anomalies. However, the turn-of-the-month effect is still relatively dominant because the results are similar in all models. The January/monthly and day-of-the-week effects show mixed results, and these anomalies are very sensitive to the model-building process. The common features of financial data can be incorporated by applying non-linear and asymmetric models and thus relaxing the assumptions of linear structural models. However, these models have different characteristics, and their application should be carefully considered as market dynamics vary from country to country. Thus, this study faces limitations based on the relatively small sample of emerging market indices as well as the exclusion of variables that might have significant explanatory power.

Another limitation of the study is the use of capitalization-weighted index data only. Because some calendar effects are related to firm size, this study does not explain the relationships between calendar effects and company properties. However, since the purpose of this study is to examine calendar anomalies more broadly, the more careful investigation should have been restricted to only one stock market or one calendar anomaly. Nonetheless, this study has systematically investigated three calendar anomalies using several methods to assess their existence's reliability critically.

Although the field of research for these anomalies is vast and has a long history, their existence or disappearance should be examined at regular intervals under dynamic market conditions. Moreover, the research among emerging markets compared to developed markets is still relatively limited due to a lack of data and less improved financial integration. Thus, this study seeks to provide more information about these calendar anomalies and the time-series properties of the emerging market stock returns. Further research ought to examine the presence of calendar anomalies using firm or industry sector data. Additionally, following Gregoriou et al. (2004), possible other studies should investigate whether these anomalies appear after accounting for transaction costs. To my knowledge, the effects of transaction costs on the appearance of calendar anomalies have been studied mainly in developed markets.

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